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Research Article

Predicting Human Reliability based on Individual's Resting Period: Effect of Physical Workload Rate

Caecilia Sri Wahyuning, Saras Atiko

Department of Industrial Engineering, Faculty of Industrial Technology, Institut Teknologi Nasional, Jl. PHH Mustopha No. 23, Bandung 40124, West Java, Indonesia

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CORRESPONDENCE

Phone : +62815-8408-8059
E-mail : caecil@itenas.ac.id

ABSTRACT

When a person is exposed to a prolonged workload, he/she enters a fatigue phase, the indication is the decline of cognitive performance that leading to human error. As an integral part of a system, human contributes to system reliability; therefore, it plays an important role in potential failure. Those, it is necessary to investigate how human reliability relates to physical workload rate, in order to predict maximum work duration to eliminate potential failure. A physical experiment involving 20 participants was conducted to generate medium workload, followed by Stroop test to observe selective attention and cognitive control as a form of cognitive performance. The physical workload was observed through energy expenditure and oxygen consumption during physical activity, and cognitive performance through response error time on the Stroop test. The usage of Weibull distribution was aimed to obtain reliabilities for each participant. There was a decline in reliability for all participants from one test to the other. Based on scale and form parameters, the prediction of resting time was based on mean time to human error (MTTHE), and from this experiment, varied MTTHE from each participant were obtained. The variation was created by differences in physical performance, cognitive capabilities, and other contributing factors such as environment and time of the implementation of the experiment. From this research, it was evident that human reliability can be utilized to predict potential failure in humans, which then implies a preventive action is necessitated to prevent failure from manifesting in the shape of taking a break/rest or reducing work rhythm. The application of human reliability in human resource management can be directed towards fatigue management and operator-related operational management.

INTRODUCTION

Physical activities involving prolonged mechanical or metabolic load have a risk of manifesting into an excessive workload, triggering worker's fatigue [1] and giving a feeling of lack of energy and tiredness [2]. Fatigue happens when demand exceeds the body's capacity; therefore, demand must adjust to both physical and mental capacity.

The shift in technologies also causes a change in workloads, from a dominant physical load to a mental load. Even so, some works still require physical activities while simultaneously requiring cognitive performance. The form of mental fatigue can be observed through the decline in work performance, that requires awareness as well as manipulation and information acquisition which were stored in memories [2]. However, mental fatigue are not just triggered by cognitive demands but also other factors such as stress, physical fatigue, and motivations.

Heavy physical workload can be inferred as one factor affecting the development of mental fatigue status because cognitive and musculoskeletal function decline often happen together [3][4]. Brain function and body composition are intertwined, with metabolically active tissue such as skeletal muscle releasing neurotrophic factors controlling brain synapses [4]. Physical workload interrupt's cognitive function and brain mental performance [3]. Therefore, high physical fatigue can significantly increase mental fatigue induction; hence cognitive performance decline indicates fatigue.

Cognitive performance is an individual indicator in the shape of decision-making results from information processing. Receiving stimuli (information) through a sensing system starts the cerebral work of information processing, which ends in the decision-making process based on said information. This performance can be observed through accuracy and speed. Works that require

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cognitive capability (works with the mental workload) usually require speed and accuracy for decision-making.

Many works require executing a task that demands cognitive capabilities, while at the same time, the workers are also involved in physical actions [5]. For example, in manufacturing industries, operators are required to finish their work (speed) while also fulfilling a quality requirement (accuracy). Human is a part of a system; therefore, individual performance reliability, which is the capability to avoid/resist work obstacles, must be recognized and controlled. Muscular parameters, mainly muscle functions, qualities, and densities, are related to certain cognitive domains (including work memories, attention, and the speed of information processing) regardless of age, levels of physical activity, education, and lifestyle [4].

Human error played a significant role in several horrible accidents, such as Chernobyl meltdown, Challenger Space Shuttle explosion, and Three Mile Island accident, and fatigue has been considered the main contributor to morbidity and mortality in the workplace and traffic [6]. This indicates that fatigue significantly affects human performance [6] physically and mentally. Therefore, as an intrinsic factor, fatigue is directly and indirectly implicated as a cause of human error[7].

Human errors are sets of failure to perform several tasks and represent human reliability conditions [6], which affect performance so that they interrupt normal operational conditions. Human reliability shows the probability of successful task performance of a human during every required step in a system operating within the minimum required time limit[8]. Inaccuracies or mistakes during decision-making can often be called human error, which occurs on almost all tasks requiring cognition. The probability of failure shows the likelihood of a human fulfilling all human functions determined during the said condition, known as human performance reliability.

Human reliability assessment (HRA) is a part of the reliability discipline that studies overall human performance during an operation. Most reliability assessment techniques are partly based on behavioral psychology, with practically reliable and useful results expected from the high-quality predictive analysis. Even so, actual quality levels depend on applying relevant findings in psychology or ergonomics and in conclusion taken from the wrong action, for example, through operational experience evaluation or simulator experiment [9].

HRA method is designed to recognize that human cognitive behavior is not related to the external character of a situation (that is, the procedure does not always involve rule-based behavior). Operators can usually adapt to different situations; they study the required behavior and gain related skills when doing repetitive actions. HRA tools calculate the possibility of human error for certain task types while calculating the effect of performance-shaping factors [9].

Philosophy on reliability and error can be traced back to the days of H.L. Williams, showing that humans as an element in reliability must be related to the prediction of a reliability system. Otherwise, the predicted value will not represent a true reliability system [10]. Since one of the attempts to improve reliability was affected by human reliability, this research attempted to study how human reliability observed through cognitive performance can be applied by measuring human error caused by physical workload rate.

Human Reliability Analysis adjusts work conditions by predicting human conditions with a cognitive performance model [11]. Almost every work has the potential of causing fatigue, in line with the work time period in regard to its intensity and individual capacity. One work interruption often mentioned is fatigue [12]. Enough rest is the only solution for fatigue, of which enough rest time and duration enables physical recovery to help with optimum work. This research intents to predict a work's resting time based on human reliability of people under a certain workload.

This paper is presented in 4 sections, starting with an introduction on the importance of this research. Section 2 describes the research methodology and followed by explanation and discussion of the result on section 3. Section 4 presents about the conclusion of this research.

METHOD

This research was a lab experiment involving several participants picked from a group of students. However, COVID-19 pandemics forced each participant's research to be done outside the laboratory. Therefore, preparations and executions were done by participants but under the supervision of the researcher team. Once done, the measurement results were delivered to the researchers. Participants here were volunteers, but before the experiment they were informed about giving their consent in this research. In our organization, experiments involving human does not usually require approval from ethics committee unless involving medical laboratory and the procedure is carried out under the supervision of the affiliated department.

In this experiment, participants were doing physical activities that induce tiredness, including running on a treadmill and riding static bicycles in the laboratory and light exercises outside the laboratory. Physical activities were done for 3 minutes, followed by 3 minutes of physical workload and performance was simultaneously. Workload and performance measurement is done 20 times; therefore, each participant spent 117 minutes (approx. 2 hours) experimenting.

Participants

Participants in this research were 20 students (10 male and 10 female) with the age range of 21-23 years with the average height of 158 (SD±7.68) cm, with details described in Table 1. All participants had low-to-medium physical (sport) activities and enjoyed gaming. Gaming and watching videos were considered low-physical activities that can be done for a long time.

Physical Workload

Workload showed the size of work demand. The increase in muscle requirements during a work activity required higher energy consumption. This energy consumption will momentarily increase after physical workload [13], declared in the work joule.

Table 1. Sample Characteristic

	Male n=10)	Female (n=10)
Age (y.o)	21.0 ± 0.54	21.3 ± 0.78
Weight (kg)	64.7 ± 12.89	55.3 ± 9.95

Work joule was obtained through measuring energy consumption during work and reducing resting consumption or basal metabolism [14]. The workload can be accepted as long as the said workload was equal to cardiorespiratory capacity during 8-hour work. Under a near-equilibrium condition, oxygen uptake (VO_2) and heart rate (HR) maintained a steady condition with constant work output [15].

In this research, the physical workloads were measured through simple HR measurement, replacing measurement of metabolism process, especially O_2 uptakes, and predicting problems with physical workload level. HR and its variability (HRV) is a method often used to evaluate workload [16] because the heartbeat responds to the change in demands quicker, therefore better representing a bodily response to the change in work demands[17].

Physiological criteria are often used to evaluate physical workloads are energy consumption (EE) during the load application and oxygen [18]. During medium physical activities, there is a linear correlation between HR and oxygen consumption[19]; therefore, oxygen consumption and HR are often used to measure physical [20]. Calculation of EE in relation to sex, age, weight, and HR can be done using equation [19].

$$EE = G(-55.0969 + 0.630HR + 0.1988W + 0.2017A) + (1-G)(-20.4022 + 0.4472HR - 0.1263W + 0.0074A) \text{ kJ/mnt} \quad (1)$$

With: HR: heart rate (*beat*/ minutes)
A : Age (years)
W : weight(kg)
G : Gender, 1 for male and 0 for female

The equation used to determine oxygen uptake (VO_2) refers to HR developed by Yuliani [13], which are:

$$VO_{2men} = -1{,}168 + 0{,}020HR - 0{,}035A + 0{,}019W \text{ (l/m)} \quad (2)$$

$$VO_{2women} = -1{,}991 + 0{,}013HR + 0{,}024W \text{ (l/m)} \quad (3)$$

with: HR: heart rate (beat/ minute)
A : Age (years)
W : Weight (kg)

Since this experiment was done independently, HR measurements were done using *Welltory: Heart Rate Monitor* apps accessed through a smartphone. This application was quite accurate because the photoplethysmography (PPG) measurement results on *Welltory* match that of Polar or ECG measurement [21].

Cognitive Performance

Humans perform various continuous tasks where tasks have limitations which will increase error probability when crossed. Energy consumption only measures physical effort level, used as a comparison only for heavy physical effort and not to study mental activity or skilled labour [14]; therefore, mental activities are observed through cognitive performance.

Human performance measures action and failure under several conditions [22]. The Stroop Color-Word Interference Test is a cognitive task used to assess executive function, especially selective attention and cognitive control of automated processes [23]. Stroop-test evaluates the psychomotor speed and cognitive flexibility by measuring the time required to identify symbols and words printed in different colours in a correct manner [24]. Therefore, this test can be used to evaluate error [25].

On the Stroop test, participants resolved conflicts immediately after the name of the colour was written in a different colour, which were conflicts between colour code and semantic code [26]. In this research, the tests were in the form of colour-word interference, where participants must pick a suitable colour button with the words that appeared even though the words were written in conflicting colours. This counts as a heavy cognitive load (colour incongruence) [27].

In this research, the Stroop test was applied through *Software Design Tools for Methods Standard and Work* (11th ed.) ver. 4.1.1.[28]. Participants, were able to download and use this app through their laptops, not requiring any special training to use it. Participants were guided through the settings and during measurement and testing by researchers.

Human Reliability

Quantitative HRA techniques refer to a human task database and related error levels to calculate the average error probability for certain tasks. These methods are focused on identifying an event or lapses and determining the general result of task analysis or incident investigation [9].

Human reliability is the success probability of someone finishing a certain task during every stage in an operating system in a determined time frame (when time is the limiting factor)[22] [9]. Potential violations during work with several limitations can happen because of human limitations, increasing error probability. This condition will cause a significant decrease in reliability [22]; therefore, the reliability of human performance is an important parameter. Human performance reliability is the reliability of humans fulfilling all human functions determined by certain conditions [22].

Reliability functions for a continuous random variable are described as [22]:

$$R_{(t)} = 1 - F_{(t)} = 1 - \int_{-\infty}^{t} f_x dx \quad (4)$$

where f(x) is the density function of human error/failure and R(t) is the reliability function.

The cumulative distribution function for continuous random variables is described as:

$$F_{(t)} = \int_{-\infty}^{t} f_{(x)} dx \quad (5)$$

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Values expected from continuous random variables are described as:

$$E_{(t)} = \mu = \int_{-\infty}^{t} t f_{(t)} dt \tag{6}$$

Weibull distribution is a random continuous variable probability distribution used to represent the physical phenomenon. The probability density function is described as:

$$f_{(t)} = \frac{\theta t^{\theta-1}}{\beta^{\theta}} e^{-\left(\frac{t}{\beta}\right)^{\theta}}, t \geq 0, \theta, \beta > 0 \tag{7}$$

where θ is a shape parameter and β is a scale parameter. From (7) and (8), the cumulative distribution function obtained is:

$$F_{(t)} = 1 - e^{-\left(\frac{t}{\beta}\right)^{\theta}} \tag{8}$$

Refering to (4) $F_{(t)} = 1 - R_{(t)}$, then:

$$R_{(t)} = e^{-\left(\frac{t}{\beta}\right)^{\theta}} \tag{9}$$

By substituting (7) to (6), distributions expected, or average values obtained from:

$$E_{(t)} = \beta \Gamma \left(\frac{1}{\theta} + 1\right) \tag{10}$$

Mean Time to Failure (MTTF) for Weibull distribution is obtained from [29]:

$$MTTF = \beta \Gamma \left(\frac{1}{\theta} + 1\right) \tag{11}$$

In this case, MTTF was a mean time to human error (MTTHE); therefore, equation can be used to determine MTTHE. In this research, an MTTHE would be determined to be used to determine resting time.

Parameters used on Weibull distribution shape parameter (θ) and scale parameters (β), with the median rank obtained from [30]:

$$Median\ rank = \frac{i - 0{,}3}{n - 0{,}4} \tag{12}$$

With:
i = Sequences of failure
n = Numbers of data

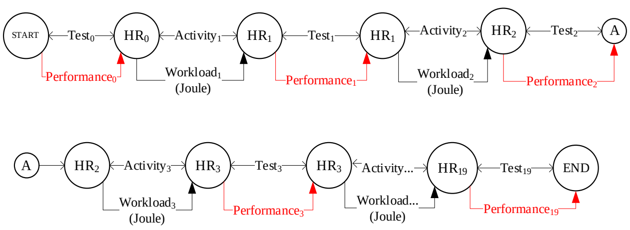

Figure 1. Experiment Design

Experiment Design

This experiment utilized the primary task method, where participants perform the Stroop test after a moderately heavy workload. The Stroop test was done 20 times in a sequence described in Figure 1. In this research, the average time for 1 Stroop test was 2 minutes; therefore, it was assumed that the Stroop test needs 2 minutes to be performed. From this, we can infer that the average time between 30 stimuli was 4 seconds. Therefore, the time between failure to response means time to human error was obtained.

Before performing the first test, participants measured heart rate before work (HR_0) as a resting HR (HR_{rest}). After the Stroop test, participants continued with moderate workload activities for 3 minutes. Heart rate is a good predictor for the moderately intensive workload (approx. 100-140bpm) [31]. Therefore, participants were expected to maintain workload at such a rate.

Participants measured their heart rate along with the Stroop test by sticking their fingers on a smartphone camera. This was done to maintain heart rate as per previous activities. Simultaneous measurement is done to avoid sudden drop of heart rate, because during stroop test all physical activities are stopped. Therefore, this procedure would be repeated 20 times to obtain 20 test results and heart rates, with total experiment time of 2 hours.

RESULTS

Physical Workload

HR measurement on participants obtained result as shown in Table 2. The average HR_{rest}, the heart rate before the experiment, was 89.2 bpm, with 3 participants starting the experiment with HR > 100 bpm. This showed that these 3 participants were on moderate workload before experiments.

Even though this was normal, the HR_{rest} of participants tend to be high (71 bpm minimum). HR_{rest} determines heart condition, physiological homeostasis, and cardiorespiratory fitness, usually ranging from 60 to 100 bpm. HR_{rest} is useful to evaluate the autonomous nervous system's physiological and clinical health, which affects autonomous controls, and a higher resting heart rate shows a reduction in parasympathetic activity [32][33][34]. One of these parasympathetic activities is the control of body activity while resting. Many prospective studies showed high HR_{rest} level

Table 2. Mean Heart Rate, Energy Expenditure and VO_{2max}

	All Participants n=20	**Male n=10**	**Female n=10**
HR_{rest}	89.2± 10.19	90.4± 12.47	87.1± 7.99
HR_{mean}	122.5± 19.08	119.7± 18.72	122.7± 20.12
Energy Expenditure (kJ/m)	34.1± 11.36	39.2± 11.39	29.1± 8.76
VO_{2max} (L/m)	1.7± 0.47	1.7± 0.44	1.6± 0.49

has negative effects on morbidity and cardiovascular conditions. VO_2max (cardiorespiratory fitness indicator) decreases as HR_{rest} increases[32]. Participants experienced decline in high physical activity for 2 years because of COVID-19 pandemic, reducing body performance. High-intensity physical activity is important to support physical performance, therefore the reduction in physical activity had an adverse effect for mental and physical health, as well as contributing to heart autonomous dysfunction [35][36][34].

Heavy workload is every activity that requires massive physical energy and is marked by high energy consumption and high pressure on the heart and lungs. Table 2 showed HR_{mean} after performing physical activities. Referring to workload classification [17], the overall workload classification for this experiment was heavy work at 120-140bpm. This condition happened because participants could not maintain their physical activities at a medium work level. The highest HR_{mean} occurred at 162.8 bpm (participant 3), which means the participant was always under an extremely heavy workload. (>160bpm). Using Welltory apps from smartphones indicated that participants could not control the activity because measurements were only done after the activity. This was not the case when using a smartwatch that can monitor heart rate during activities.

If we refer to workload classification [17], all participants were on heavy workload levels ranging from 30-39 kJ/min, which was also true for male participants. Female participants were classified as medium work at 20-29 kJ/min, bordering on heavy work. This was also shown in oxygen consumption (Table 2). Referring to workload assessment [14], the oxygen consumption value of participants was considered to be high at 1.5-2 litre/min.

All participants experienced changes in physiological function from the start to the end of the experiment, observed from the change in oxygen consumption, oxygen uptake, and heart rate. These variables were used to assess a person's response to workloads or to assess demands applied by experiments [17].

Cognitive Performance

Table 3 shows the failure percentage experienced by 20 participants. Participants carried out this experiment individually, the Stroop test was done simultaneously with heart rate measurement. During every test, participants responded to 30 stimuli, accounting for 600 responses for the entire test. The result shows the largest failure percentage happened on participant 5, where all tests failed, and 93 response failures occurred. For instance, participants 2 produced 11 response failures from 20 tests obtained, amounting to 1.83%.

The Stroop test in this research with color-words stimulus and interference were included in high cognitive load category [37]. Cognitive load tends to increase as an individual performed difficult task, multitasking, using perceptual and cognitive resources (visual and auditory perception, memory and attention) [36]. As a result, Excessive mental effort will trigger mental fatigue that affects performance. Fatigue on participants was an accumulation of muscle and mental fatigue caused by heavy cognitive load, affecting performance in every test. In general, the main symptoms of fatigue are the lack of physical and mental effort, feeling heavy, drowsiness, and general fatigue. [14]. Boredom and tiredness caused a decline in work performance. Because of fatigue, the participants were dealing with new information caused a hurry-up syndrome [6] [23].

Pandemic played part in changing lifestyle, causing people to be more sedentary [34], changing mood with the increasing feeling of declining capabilities of performing mental/physical task [2], affecting physical performance caused by the decline in physical activity. Consequently, it can be seen in Table 3 that 12 from 20 participants suffering over 50% failures during the test.

Human Reliability

From MTTHE, by using median rank, we obtained the shape parameter (θ) and scale parameter (β) for participants, as shown in Table 4. Participants 1, 12, and 17 did not have scale and shape parameters because they only made fewer than two responses, as shown in Table 5. The scale and form parametric numbers for participants 1, 12, and 17 could not be determined, because these participants failed to respond less than twice.

Based on equation (8) and shape parameter (θ), and scale parameter (β) in Table 4, reliability can be obtained as shown in Table 5. Initial reliability (R_0) is participants' reliability during the first test, while R_t are the average reliabilities after the entire test.

Table 3. Failure Percentage of Test and Total Response

Participants	Tests n=20	Response n=600	Participants	Tests n=20	Response n=600
1	10.0	0.33	11	75.0	4.67
2	30.0	1.83	12	0.0	0.0
3	65.0	4.50	13	25.0	1.00
4	90.0	5.50	14	65.0	3.50
5	100.0	15.50	15	65.0	4.67
6	75.0	5.00	16	50.0	1.83
7	75.0	5.67	17	5.0	0.17
8	70.0	4.67	18	20.0	0.67
9	45.0	1.50	19	45.0	1.67
10	95.0	5.67	20	50.0	2.67

Table 4. Shape Parameter (θ) and Scale Parameter (β).

Participants	θ	β	Participants	θ	β
1	-	-	11	216.1	0.7862
2	516.3	0.5857	12	-	-
3	163.4	0.6186	13	1774.0	0.400
4	195.6	0.7726	14	273.5	0.5071
5	48.0	0.7108	15	181.3	0.,6215
6	202.0	0.8057	16	988.6	0.5313
7	115.6	0.5992	17	-	-
8	189.5	0.6766	18	2996.3	1.482
9	803.6	0.5186	19	757.4	0.5144
10	200.2	0.6721	20	351.8	0.7983

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Table 5. Initial reliability (R_0) and mean reliability (R_t) (%)

Participants	R_0	R_t	**Participants**	R_0	R_t
1	-	-	11	70.6	5.0
2	76.4	12.4	12	-	-
3	60.5	4.6	13	78.2	32.5
4	35.9	1.8	14	64.7	8.6
5	35.9	1.8	15	62.5	5.0
6	69.9	4.7	16	80.6	21.8
7	53.6	3.7	17	-	-
8	64.9	4.9	18	99.6	40.2
9	78.1	19.2	19	77.3	18.5
10	65.8	5.1	20	79.0	7.2

Table 6. Average Mean Time to Human Error (MTTHE)

Participant	**MTTHE (minute)**	**Participant**	**MTTHE (minute)**
1	-	11	4.1
2	13.4	12	-
3	3.9	13	98.0
4	3.8	14	8.9
5	1.0	15	4.3
6	3.8	16	29.6
7	2.9	17	
8	4.1	18	45.1
9	25.1	19	24.0
10	4.4	20	6.7

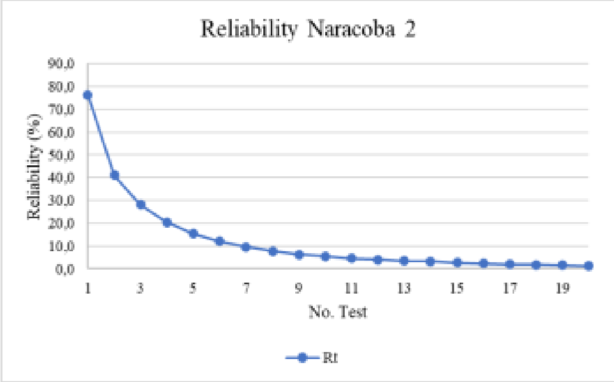
There was a decline in every test; for example, a decline occurred in participant 2 (female), shown in Figure 2a and participant 8 (male) in Figure 2b. A drastic decline was observed on participant 2 where $R_{(0)}$ = 76.4%, with $R_{(1)}$= 41.2%, $R_{(3)}$= 28.0%, $R_{(4)}$= 20.4%, etc. Participant 2 suffered failure on the fourth test at stimuli 5 and 25. On test 4, participant 2's reliability is $R_{(4)}$= 20.4%.

Participant 18 had $R_{(0)}$ = 99.6% with a gently sloping decline in reliability, with 3 out of 600 responses failing and the first failure occurring on test 3 at stimulus 23. The next failure occurred on test 7 at stimulus 28, and the last failure occurred on test 17 at stimulus 20. Participant 8's reliability on test 1, 3 and 17 were $R_{(3)}$= 87,2%, $R_{(7)}$= 52.6%, $R_{(17)}$= 9.5%.

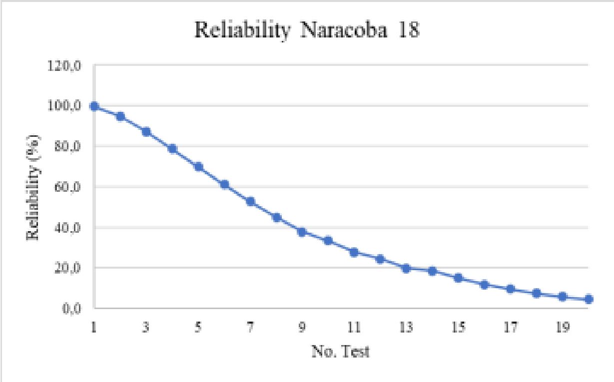
Mean Time To Human Error

Calculation of human reliability calculates error probability for certain tasks while calculating the performance shaping factor (PSF) effect. MTTHE are the mean time to human error, indicating that in between these times, there are lower possibilities of failure/errors. However, in manufacturing industries, failure can cause product defects or safety issues. Therefore, MTTHE must be determined to stop operations before a failure occurs, giving time for operators to recover or to return to a tolerable reliable condition.

MTTHE depends on failure probability, and human reliability is determined by scale and shape parameters. With equation (11), MTTHE can be determined using both factors in Table 4; therefore, MTTHE for each participant can be obtained as shown in Table 6.



(a) Participant 2



(b) Participant 18

Figure 2. A decline in the reliability of female (a) and male participants (b)

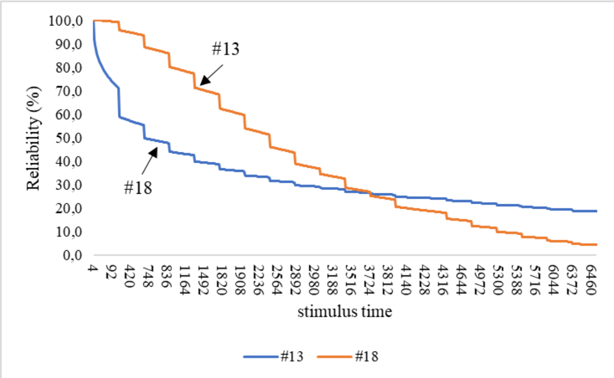


Figure 3. The difference in 2 participants' reliability rate

Although not specifically studied, based on the analysis above, it is shown that the difference in MTTHE also shows the difference in reliability, which is affected by physical performance, cognitive capabilities, experiment time, and environment. MTTHE for participants 2 and 18 are 13.4 minutes and 45.1 minutes, respectively. This means human error on participant 2 will occur every 13.4 minutes, and participant 18 will make errors every 45.1 minutes. The longest MTTHE is with participant 13, at 98 minutes.

The number of errors on participants 13 and 18 were 4 and 3, respectively. Even though participant 13 had an $R_{(0)}$ of 78.2%), smaller than participant 18 (99.6%), MTTHE of participant 13 was higher because participant 18 made errors earlier than participant 13, therefore affecting scale and shape parameter values in Table 6. Illustrated reliability rate of both participants

can be seen in Figure 3. It is seen that participant 13 has the shallower decline in reliability; therefore participant 13 has longer MTTHE. On that base, MTTHE cannot be generalized, but this approach can be used to determine resting periods.
System reliability is seen as the system's capability to do required functions. This is more than just a number but a property of a complex system [9]. Human as a system component contributes to the man-machine system's success; therefore, a failure in the system can be caused by human error. Thus, quantifying human error is needed to consider the effects of human error on system reliability [33].

The basic difference between technical and human reliability is data processing and achieving goals. The probability of misconduct from human activity can be high, but the likelihood of not obtaining final results is low [9]. However, the human factor still plays an important role because human errors are one of the potential dangers as well as the cause of product defects. Not every system component works as intended; therefore, individual components can contribute to system failure through errors of omission and commission by doing an unexpected act [37].

Safety and failure potentials are integral to the prevention and depend on system reliability. In the development of HRA, 8 PSFs are used to assess error-inducing conditions by considering human error probabilities: time availability, complexity, stress, experience/training, ergonomics/human-machine interaction, work procedure, fitness-for-duty, and work process [33].

Conceptually, reliability engineering includes calculation/qualification of the possibility of individual error/component failure and the possible correlations, determining the effect of individual error/component failure on a system, and developing a strategy to avoid said error/failure or to reduce the error/failure and/or its effect [37]. In this research, the resting period prediction is one effort to avoid errors, assuming operators are making proper recovery after fatigue during the resting period. From this rest, operators were expected to recover their reliability to the initial condition or after the previous break. In other words, the rest period reduced the decline rate of reliability of the operator.

Limitations

This research was done during a pandemic; therefore, there were limitations from a lab experiment under the researcher's supervision—the method shifts to independent experiments observed by the researcher through video conference.

The tool limitations mean participants cannot control the workload. The usage of apps through smartphones was done to help participants individually check their HR. Therefore, the next research must be done with more appropriate tools to support the needs of the research. Furthermore, this research can be done through field study by applying it to a real work.

Measurement using Welltory apps was carried out by sticking fingers on smartphone camera, therefore participants are required to remain still (stopping all physical activity). This caused decrease in heart rate, as opposed to measurements using smartwatch.
Human errors are affected by environment, the complexity of task/information load of the experiment, moderation effect of response time, cognitive capabilities, and stress level. Therefore, further research is necessary to determine how those factors affect humans. According to the research goal, this research can be developed for human resource management towards fatigue management, work scheduling-related management, and operator-related production management.

CONCLUSIONS

The effect of increased physical workload is in the decline of performance, with cognitive performance being one of them. Human error as one form of cognitive performance decline can manifest in forms of lapses/mistake on decision making which can cause accidents or product failure. From this research, a human reliability-based work/activity hour duration was obtained to reduce potential errors. This research needs further development to obtain proper rest time duration to improve reliability in relation with workloads.

Momentarily after physical work, energy consumption (work joule) spiked instantly, which showed stress levels on the body, especially during hard work. An increase in heartbeat followed by changes in other internal organs caused an increase in activation of the learning process and memory, increasing mental fatigue. The level of cognitive load affected visual information processing and increases errors/failures to fulfil several demands, heading towards a reduction in reliability.

Human reliability can predict human failures; therefore, a preventive measure is needed to prevent failure by stopping work or reducing work rhythm. Therefore, human reliability plays an important role in human resources with goals to improve safety and productivity through the application of human reliability in human resource management, where this can be aimed at fatigue management to improve company productivity and the living quality of the operators.

REFERENCES

[1] J. R. Wilson and S. Sharples, Evaluation of Human Work, 4th Ed. Boca Raton, 2015. https://doi.org/10.1201/b18362

[2] Boolani and M. Manierre, "An exploratory multivariate study examining correlates of trait mental and physical fatigue and energy," Fatigue, vol. 7, no. 1, pp. 29–40, Jan. 2019, https://doi.org/10.1080/21641846.2019.1573790.

[3] X. Xing, B. Zhong, H. Luo, T. Rose, J. Li, and M. F. Antwi-Afari, "Effects of physical fatigue on the induction of mental fatigue of construction workers: A pilot study based on a neurophysiological approach," Autom Constr, vol. 120, Dec. 2020, https://doi.org/10.1016/j.autcon.2020.103381.

[4] S. X. Sui, J. Balanta-Melo, J. A. Pasco, and L. I. Plotkin, "Musculoskeletal Deficits and Cognitive Impairment: Epidemiological Evidence and Biological Mechanisms," Curr Osteoporos Rep, Jun. 2022, https://doi.org/10.1007/s11914-022-00736-9.

 DOI: 10.25077/josi.v21.n2.p66-74.2022

[5] R. K. Mehta and R. Parasuraman, "Neuroergonomics: A review of applications to physical and cognitive work," Frontiers in Human Neuroscience, vol. 7, no. DEC. Frontiers Media S. A., Dec. 23, 2013. https://doi.org/10.3389/fnhum.2013.00889.

[6] M. Rasmussen and K. Laumann, "The evaluation of fatigue as a performance shaping factor in the Petro-HRA method," Reliab Eng Syst Saf, 2018, https://doi.org/10.1016/j.ress.2018.06.015.

[7] L. M. Barker Steege and M. A. Nussbaum, "Dimensions of Fatigue as Predictors of Performance: A Structural Equation Modeling Approach Among Registered Nurses," IIE Trans Occup, vol. 1, no. 1, pp. 16–30, Jan. 2013, https://doi.org/10.1080/21577323.2011.637153.

[8] Balbir S. Dhillon, Safety, Reliability, Human Factors, and Human Error in Nuclear Power Plants. Boca Raton, 2013.

[9] M. Havlikova, M. Jirgl, and Z. Bradac, "Human reliability in Man-Machine Systems," in Procedia Engineering, 2015, vol. 100, no. January, pp. 1207–1214. https://doi.org/10.1016/j.proeng.2015.01.485.

[10] B. Dhillon, "Human Reliability, Error, and Human Factors in Engineering Maintenance: with Reference to Aviation and Power Generation," 2009. https://doi.org/10.1201/9781439803844.

[11] R. L. Boring et al., "Is human reliability relevant to human factors?," in Proceedings of the Human Factors and Ergonomics Society, 2009, vol. 1, pp. 610–614. https://doi.org/10.1518/107118109X12524442635987.

[12] S. Lee and J. K. Kim, "Factors contributing to the risk of airline pilot fatigue," J Air Transp Manag, vol. 67, pp. 197–207, Mar. 2018, https://doi.org/10.1016/j.jairtraman.2017.12.009.

[13] C. Sri Wahyuning and D. Budi Laksemi, "Kajian Pengaruh Heat stress terhadap Beban Kerja FIsik Berat pada Kegiatan Lapangan," in Seminar Nasional Teknik dan Manajemen Industri dan Call for Paper (SENTEKMI 2021), Vol. 1, No. 1, Nov. 2021, vol. 1, pp. 167–174. https://doi.org/10.28932/sentekmi2021.v1i1.71.

[14] Karl H.E Kroemer and Etienne Grandjean, Fitting the Task to the Human: A Textbook of Occupational Ergonomics, Fifth Edition, 5th ed. Taylor & Francis Ltd., 2009.

[15] H. C. Wu and M. J. J. Wang, "Relationship between maximum acceptable work time and physical workload," Ergonomics, vol. 45, no. 4, pp. 280–289, Mar. 2002, https://doi.org/10.1080/00140130210123499.

[16] C. Sri Wahyuning, I. S. Rachmatiah, and I. Z. Sutalaksana, "Pengaruh Lingkungan Kerja Kabin Lokomotif Terhadap Tingkat Stres Dan Beban Kerja Mental Masinis Secara Fisiologis," Jurnal Sistem Teknik Industri, vol. 19, no. 1, 2017. https://doi.org/10.32734/jsti.v19i1.362.

[17] K. H. E. Kroemer, H. J. Kroemer, and K. E. Kroemer-Elbert, Engineering Physiology. Bases of Human Factors Engineering/ Ergonomics, 5th ed. Switzerland Ag: Springer Nature, 2020. https://doi.org/10.1007/978-3-030-40627-1.

[18] Zenija Roja, Henrijs Kalkis, Sandis Babris, Inara Roja, Kristine Bokse, and Ansis Ventins, "Physical Workload Analysis in Processing Operations: Metal Processing Manufacturing," in Advances in Physical Ergonomics and Human Factors, R. Goonetilleke and W. Karwowski, Eds. Springer Nature, 2019, pp. 14–21. [Online]. Available: http://www.springer.com/series/11156. .https://doi.org/10.1007/978-3-030-20142-5_2

[19] L. R. Keytel et al., "Prediction of energy expenditure from heart rate monitoring during submaximal exercise," J Sports Sci, vol. 23, no. 3, pp. 289–297, Mar. 2005, https://doi.org/10.1080/02640410470001730089.

[20] C. D. Wickens, S. E. Gordon, Yili. Liu, and John. Lee, An introduction to human factors engineering. Pearson Education Limited, 2014.

[21] D. J. Plews, B. Scott, M. Altini, M. Wood, A. E. Kilding, and P. B. Laursen, "Comparison of heart-rate-variability recording with smartphone photoplethysmography, polar H7 chest strap, and electrocardiography," Int J Sports Physiol Perform, vol. 12, no. 10, pp. 1324–1328, Nov. 2017, https://doi.org/10.1123/ijspp.2016-0668.

[22] B. S. Dhillon, Human Reliability, Error, and Human Factors in Power Generation. Switzerland: Springer International Publishing, 2014. [Online]. Available: http://www.springer.com/series/6917. https://doi.org/10.1007/978-3-319-04019-6.

[23] R. Vazan, D. Filcikova, and B. Mravec, "Effect of the Stroop test performed in supine position on the heart rate variability in both genders," Auton Neurosci, vol. 208, pp. 156–160, Dec. 2017, https://doi.org/10.1016/j.autneu.2017.10.009.

[24] M. Cunha-Silva et al., "EncephalApp Stroop Test validation for the screening of minimal hepatic encephalopathy in Brazil," Ann Hepatol, vol. 27, no. 1, Jan. 2022, https://doi.org/10.1016/j.aohep.2021.100543.

[25] A. K. Miller, "Examining the Errors and Self-Corrections on the Stroop Test," 2010. [Online]. Available: https://engagedscholarship.csuohio.edu/etdarchive

[26] C. Collet, C. Petit, A. Priez, and A. Dittmar, "Stroop color-word test, arousal, electrodermal activity and performance in a critical driving situation," Biol Psychol, vol. 69, no. 2, pp. 195–203, 2005, https://doi.org/10.1016/j.biopsycho.2004.07.003.

[27] L. Cabañero Gómez, R. Hervás, I. González, and V. Villarreal, "Studying the generalisability of cognitive load measured with EEG," Biomed Signal Process Control, vol. 70, Sep. 2021, https://doi.org/10.1016/j.bspc.2021.103032.

[28] B. W. Niebel, A. Freivalds, and B. W. Container of (work): Niebel, Niebel's methods, standards, and work design.

[29] Charles E. Ebeling, An Introduction To Reliability and Maintainability Engineering. McGraw-Hill, 1997.

[30] J. D. Campbell and A. K. S. (Andrew K. S. Jardine, Maintenance excellence: optimizing equipment life-cycle decisions. M. Dekker, 2001.

[31] Martin Helander, A Guide to Human factors and Ergonomics Second Edition, 2nd ed. Boca Raton: CRC, Taylor & Francis Group, 2005.

[32] S. J. Kang, G. C. Ha, and K. J. Ko, "Association between resting heart rate, metabolic syndrome and cardiorespiratory fitness in Korean male adults," J Exerc Sci Fit, vol. 15, no. 1, pp. 27–31, Jun. 2017, https://doi.org/10.1016/j.jesf.2017.06.001.

[33] R. S. Mohril, B. S. Solanki, M. S. Kulkarni, and B. K. Lad, "Residual life prediction in the presence of human error using machine learning," in IFAC-PapersOnLine, 2020, vol. 53, no. 3, pp. 119–124. https://doi.org/10.1016/j.ifacol.2020.11.019.

[34] M. Nataraj, M. K. Sinha, A. Bhat, and K. Vaishali, "Correlation between physical activity, cardiorespiratory fitness and heart rate variability among young overweight adults," J Taibah Univ Med Sci, vol. 17, no. 2, pp. 304–310, Apr. 2022, https://doi.org/10.1016/j.jtumed.2021.11.011.

[35] J. Meyer et al., "Joint prevalence of physical activity and sitting time during COVID-19 among US adults in April 2020," Prev Med Rep, vol. 20, Dec. 2020, https://doi.org/10.1016/j.pmedr.2020.101256.

[36] K. Pettee Gabriel et al., "Associations of accelerometer-determined sedentary behavior and physical activity with physical performance outcomes by race/ethnicity in older women," Prev Med Rep, vol. 23, Sep. 2021, https://doi.org/10.1016/j.pmedr.2021.101408.

[37] V. Volovoi, "System Reliability at the Crossroads," ISRN Applied Mathematics, vol. 2012, pp. 1–36, Dec. 2012, https://doi.org/10.5402/2012/850686.

AUTHOR(S) BIOGRAPHY

Dr. Caecilia Sri Wahyuning ST. MT.
Academic staff at Department of Industrial Engineering of Institut Teknologi Nasional, Bandung. Expert in human factors, product design, and Work Health & Safety.

Saras Atiko ST.
Bachelor's degree graduate from Department of Industrial Engineering, Institut Teknologi Nasional, Bandung, in 2022.

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