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Trends, relationship, and model of selected service sector workers in Malaysia: Physiological responses of mental workload and mental fatigue during performing real-time tasks

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Abstract

Service sector is a job that is considered exposed to high mental demand. There is lack of technique to measure issues related to the mental workload and mental fatigue levels among workers. Moreover, no studies have yet developed a model to predict mental fatigue especially for service sector workers. It is necessary to investigate mental workload and mental fatigue in real time working activities. The main purpose of this study was to identify the trends and relationship between mental workload and mental fatigue level among service sector workers. Ten participants with a mean age of 35.00±8.62 (SD) years took part in the study. Two experiments in Without Rest (WoR) and With Rest (WR) segments involving data entry and arithmetic tasks were conducted. Physiological measures using Electroencephalogram (EEG), Electrooculogram (EOG) and heart rate (HR) were assessed while participants were performing the tasks. The result shows that EEG alpha signal was significantly higher at the end of WR compared to WoR segment ($p<0.05$). Comparison between WoR and WR segments for each task show that HR of WR tasks were significantly lower in all tasks ($p<0.05$). This study developed seven mental workload and mental fatigue conceptual models with strong variables correlations ($r>0.05$) to evaluate the variability of both parts of two types of activities, namely, data entry and arithmetic tasks. The findings highlighted that validated parameters and methods for mental fatigue and mental workload measures are brain signals and heart rate monitoring, and task performance measure. Significant findings of the study could be as a reference for organizations to plan and manage resources by optimizing mental workload condition and minimizing mental fatigue occurrence.

Keywords: Mental workload, mental fatigue, task performance, service sector, regression.

1 Introduction

Malaysia's service industry is anticipated to grow as a result of increased foreign investment and natural resource use. The expansion of Malaysia's service industry is anticipated to help create employment and strengthen the economy as the country strives to become a high-income country. However, as a result of this rapid progress, workers may face an even greater risk at work. From statistics reported by Department of Statistics Malaysia, the national occupational accident rate in Malaysia for year 2020 is 2.18 (per 1000 workers) and it was found that service sectors recorded the second highest number of occupational accidents in year 2020 (8,008 cases) after manufacturing sector. One of the main risks that contribute to occupational accidents is excessive workload which requires high mental, physical and emotional demands from workers. This excessive workload results in mental fatigue [1-3].

Service sector is considered as job with high exposure to high mental demand. It is a people-oriented sector that requires a lot of human-human and human-machine interactions. As the industries grows, competition between companies is intense, thus, employees are expected to perform well to ensure efficiency of the services. In short, the better the employee performance, the greater the customer satisfaction and loyalty will be [4, 5]. Amongst the service activities that are expected to give high mental workload are such as operators, telemarketers, office workers and those who are in the transportation sector (e.g., road, railway track and airway). These services can cause mental fatigue and consequently increase the risk of accidents [6-10].

Based on the Malaysia Social Security Organization, the number of occupational accidents grew between 1996 and 2011. During that period, it was discovered that over 90% of industrial accidents were caused by human error [11]. Human error is defined as any unsafe act made by a person, which has substantial adverse impacts in the workplace [12]. The effect of mental fatigue has been investigated in various industries that involve tasks with human–machine interaction, such as the road transportation [13, 14], construction [15], aviation [16], and nuclear power industries [17]. However, few studies have attempted to empirically investigate this issue in the service industry of Malaysia [4, 18].

Mental workload is the interaction between two factors namely the task demand and individual mental capacity [19, 20]. Whereas there is no general definition of mental fatigue established by the scientific population [21]. Grandjean [22] defined mental fatigue as a continuing and increasing process of reluctance for any effort, reduced efficiency, and alertness, and weakened mental performance. Thus the term mental fatigue covers the decline of mental performance because of mental or physical activity [23]. Mental fatigue is also defined as the subjective nature of drowsiness [24]. Mental fatigue at work is an ordinary daily occurrence. Numerous people start to demonstrate signs of mental fatigue in daily work resulting in tasks appearing more difficult, attentiveness is low, and errors increasing. Mental fatigue has various consequences on brain functions. The main consequence is on persistent attention or vigilance [21]. Nevertheless, in the case of severe fatigue the person's performance could be affected at work as well as at home. Furthermore, severe long-term fatigue may result in sick leave and work disability.

It is critical for each individual to have an acceptable amount of mental burden. If the mental workload is either too high or too low for most human operators, the performance indicator will be decreased [25]. In a high-complexity, high-demand situation, an individual experiences slow information processing as this situation surpasses his capabilities [26]. If the task demand exceeds available resources, the mental workload level is considered overloaded [27]. In this condition, excessive mental workload causes mental fatigue and strongly linked with performance decreases or an increase in the risk of accidents [2]. To illustrate the relationship, as mental workload increases, the risks of mental fatigue and reduced productivity also increases. On the other hand, individual will become bored and more prone to making mistakes if their mental workload is lower than it should be [28].

Several previous studies proved that research on mental workload and mental fatigue are very important. Hwang et al. [25] developed an early warning model that allows the operator or supervisor to monitor the operator's mental workload by a physiological indicator. Meanwhile, Raskin [29] stated that human-computer interface usability can be strengthened by mental workload measures. In addition, monitoring human operator mental workload also helps in designing appropriate adaptive automation strategies [30]. Mental fatigue has been investigated extensively for pilots, air traffic controllers and various vehicle operators. Numbers of studies utilize analysis of variance to determine whether there are any statistically significant differences between the means of three or more independent tasks assigned to worker. However, investigation of mental fatigue on workers in the industry is still lacking. Mental fatigue in industry is frequently associated with reduced efficiency and hesitation in the effort. It is essential to control fatigue in the industry and its harmful effects on workers, as increasing mental fatigue results in the form of reduced output in the workplace and may cause critical errors in the worst cases.

There is a lack of data on mental workload and mental fatigue conditions of service sectors workers in Malaysia. Moreover, no studies have yet developed a model to predict mental fatigue especially for service sector workers. Also, there is a lack of documentation on the control measure suitability and effectiveness of mental workload and mental fatigue in the country. This study will fill the gap and will be very important in helping employers or managers design the job in accordance with workers' capabilities. Thus, the aim of this study is to identify the trends and relationship between mental workload and mental fatigue level among service sector workers. Secondly, the objective was to develop a mental workload/mental fatigue level model. The scope of this study is focused on selected sectors which are service sector office workers in government agencies in Malaysia.

2 Methods

Experiments were conducted in this study to complete the study's objectives which involved real task of the targeted group. The University of Malaya Research Ethics Committee (UMREC) has given its approval to the research process.

2.1 Participants

Ten office workers participated voluntarily. The determination of the sample size for this study was made with reference to similar works on mental workload and mental fatigue [3,15,21,25,28] where they showed that 8-15 participants were sufficient and appropriate for an experimental study to provide significant output for physiological measurements. Volunteers had to meet certain criteria to participate, including having at least 5 years of work experience, normal to corrected-to-normal vision, and computer literacy.

Additionally, volunteers must be familiar with office-type work (i.e., data entry and arithmetic tasks) and be used to working regular office shifts from 8am to 5pm. The day before becoming the experimental participant, all participants were asked to make sure they got enough rest and sleep. This was confirmed by enquiring on the number of hours slept before starting the experiment. All participants stated that they did not have any injuries or mental or musculoskeletal disorders that affected their daily life recently.

2.2 Experimental setup

The experimental setup shown in Fig. 1 was prepared in an office room in NIOSH Headquarters. In the office computer workstation setup, a computer set, a video camera and EEG set were arranged accordingly. The video camera recorded the participants while performing the tasks from the side view and synchronized the timing with the EEG data.

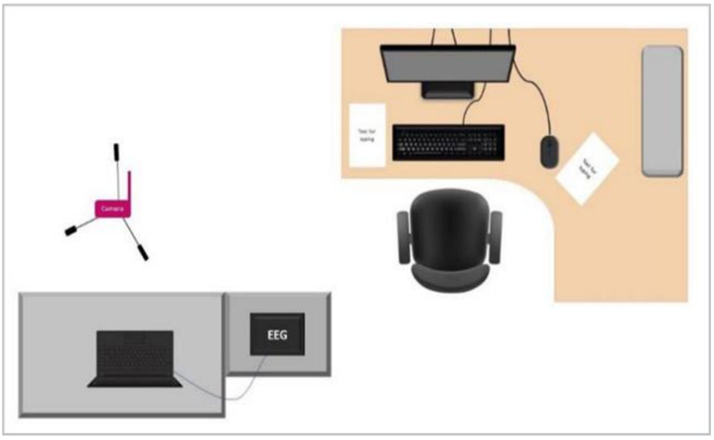

Fig. 1. The office computer workstation experimental setup

2.3 Mental workload and mental fatigue measures– Electroencephalogram (EEG), Electrooculogram (EOG) and heart rate

MP150 System and BIOPAC EEG100C with Acq-Knowledge 4.0 software were used to acquire and analyse the brain activity. Fig. 2 (left) shows the stretch AgCl electrode-cap [31]. EOG were utilized to detect and remove blink artifacts in the signals. The electrodes were examined before each assessment to ensure that the impedance was less than 5 kΩ. The signals were recorded using a bipolar recording technique. The BIOPAC EEG100C amplifiers amplify signals recorded at 1000 samples/s. Based on previous studies [23], electrodes location considered in this study were P3, P4, O1, O2, FZ and PZ, (Fig. 2 (right)).

There significant bands were considered in this study namely Theta (4–7.99 Hz), alpha (8–12.99 Hz), and beta (13–30 Hz). The result was then standardized using Eq. 1, 2, and 3 to obtain the bands relative powers:

$$RP\theta = \frac{\int_{fl}^{fh} Sx(f)\,df}{\int_{0}^{fmax} Sx(f)\,df} \times 100 \tag{1}$$

where $fmax$ = 95Hz, fl = 4Hz, fh = 7.99 Hz;

$$RP\alpha = \frac{\int_{fl}^{fh} Sx(f)\,df}{\int_{0}^{fmax} Sx(f)\,df} \times 100 \tag{2}$$

where $fmax$ = 95Hz, fl = 8Hz, fh = 12.99 Hz;

$$RP\beta = \frac{\int_{fl}^{fh} Sx(f)\,df}{\int_{0}^{fmax} Sx(f)\,df} \times 100 \tag{3}$$

where $fmax$ = 95Hz, fl = 13Hz, fh = 30 Hz.

The participants were also equipped with the Actiheart device. The Actiheart is the first commercially available device that combines a HR monitor and accelerometer into a single unit (Fig. 3). The Actiheart is a compact, chest-worn monitoring device that records heart rate, Inter-Beat-Interval (IBI), and physical activity in one combined, lightweight waterproof unit. It is designed for capturing heart rate variability (HRV) data and for calculating and measuring Activity Energy Expenditure [32, 33].

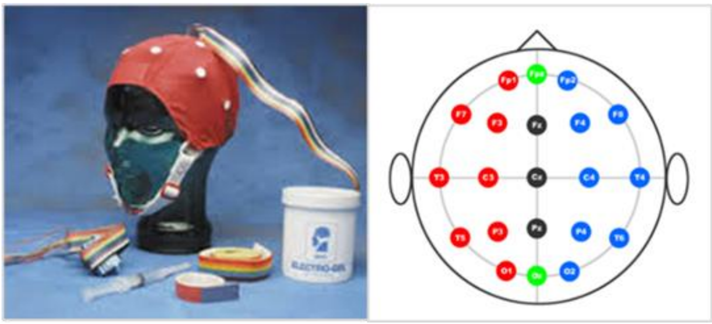

Fig. 2. Electroencephalogram components (left) (Picture source: BIOPAC Systems Inc., 2017) and locations of the EEG placements (right).

Fig. 3. Actiheart device for HR measurement

2.4 Task performance measures

Details of tasks for the main experiment are presented in Table 1. Two main tasks were prepared for this experiment, namely data entry task (Task 1) and arithmetic task (Task 2) which took an hour to complete each task. The tasks design intended to elicit different levels of mental workload. The total durations of the experiment were two hours and to analyze Time-on-Task (ToT) trends and effects on the mental workload and mental fatigue measures, the duration was averaged per test by subdivisions of nearly 1 min each corresponding to 20 segments for Task 1 and 30 segments for Task 2. Both tasks were performed with two different segments, namely Without Rest (WoR) and With Rest (WR) segment.

Table 1. Task performance measures and derivations for the main experiment

No.	Task	Duration	Performance measure	Description/ derivation
1a	Copying the journal in English language	20 mins	Accuracy: Typed words	The number of correctly typed words minus typing errors divided by the total number of words typed.
			Efficiency: Total number of words	The number of words copied divided by the standard of Average Typing Speed (40 words per minute)
1b	Typing texts from book in Malay language	20 mins	Accuracy: Format	The number of three types of format elements (font, spacing, layout)
			Efficiency: Total number of words	The total number of typed words divided by the standard of Average Typing Speed (40 words per minute)
1c	Replying to emails	20 mins	Accuracy: Email content	The number of emails replied with the correct content on the specific subject
			Efficiency: Completion rates	The number of emails replied divided by the total number of emails assigned in the entire task.
2a	Solving a simple budget	30 mins	Accuracy: Total number of correct answers	Number of correct answers based on the budget given
			Efficiency: Completion rates	The number of answers replied divided by the total number of budgets assigned in the entire task.
2b	Solving a difficult budget	30 mins	Accuracy: Total number of correct answers	Number of correct answers based on the budget given
			Efficiency: Completion rates	The number of answers replied divided by the total number of budgets assigned in the entire task.

2.5 Experimental procedure

When participants arrived at the setup station, they were instructed on the experiment details. The informed consent form and demographic questionnaire were completed after they had fully comprehended all the details. The measurement equipment was then set up in the appropriate locations. Following that, they were all given the opportunity to become acquainted with the computer workstation and environment. The flow of the experimental procedure for both segments are presented in Fig. 4 and 5. The duration of rest for the WR segment were designed based on reference on a few previous studies [34-36]. During the rest period, participants took a break from doing any computer tasks and were allowed to perform simple stretching movements, look out the window at the green scenery and even close their eyes.

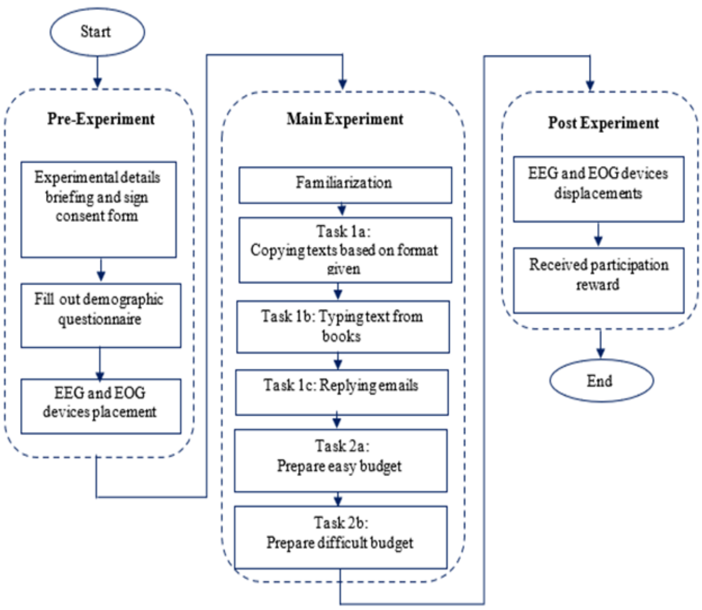

Fig. 4. Main experimental procedure for the Without rest segment

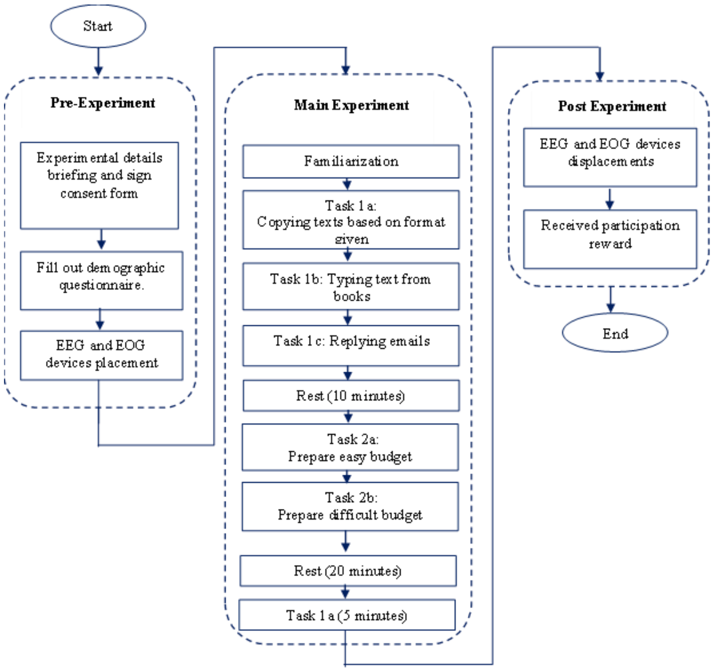

Fig. 5. Main experimental procedure for the With rest segment

2.6 Statistical analysis

The IBM Statistical Package for Social Science (SPSS) for Windows version 23.0 was used to conduct the research analysis, which was based on the objectives (Armonk, NY: IBM Corp). Skewness and kurtosis test were conducted on all data sets prior to the main data analysis. The study was based on the hypothesis that different types of tasks will result in varied mental workloads, which will alter the pattern of mental fatigue.

The mental effort and mental tiredness variables were analyzed using a mixed model repeated measures ANOVA, and Pearson correlation to determine if the objectives were met. These parametric statistical analysis methods were selected as the experimental data were normally distributed. The repeated measure ANOVA investigates any overall differences between related means under three or more different conditions while the Pearson correlation examines the strength and direction of association that exists between two variables measured.

Raw data were obtained from the Acq-Knowledge 4.0 software (BIOPAC Systems Inc.), analyzed, and normalized into relative power bands for the EEG output. The repeated measures ANOVA in the mixed model comprises repeated measures between the subject's factor and task variables. The relationship between mental workload and mental fatigue measures were analyzed using Pearson correlation. Multiple linear regression was used to develop the mental workload and mental fatigue models.

3 Results.

Experimental results were reported in four sub-sections based on the objectives of the study, which presenting the mental workload and mental fatigue. Ten participants participated in experiment with average age and work experience of the participants were 35.00 ± 8.62 (SD) and 10.80 ± 7.41 (SD) years, respectively.

3.1 EEG frequency bands physiological measures of mental workload and mental fatigue

The results of the 2×2 repeated measure ANOVA with the type of task (three types; Task 1a, Task 1b and Task 1c) and time on task (ToT) (M1 to M20) as within subject factors for EEG frequency bands of WoR segments are presented in this section. The results of the 2×2 repeated measure ANOVA with the type of task (two types; Task 2a and Task 2b) and time on task (ToT) (M1 to M30) as within subject factors for EEG frequency bands are reported in Table 2. The same analysis was done for With Rest segment and is reported in Table 3.

Table 2. Electroencephalography RPθ, RPα and RPβ results of the participants based on task WoR

Task	Channel location	Factor (s)	RPθ	RPa	RPβ
			p	p	p
		Type of Task	0.998	0.613	0.325
	F_ZP_Z	ToT	0.121	0.000*	0.001*
		Type of Task *Tot	0.279	0.021*	0.000*
		Type of Task	0.124	0.049*	0.009*
1	O_1O_2	ToT	0.732	0.000*	0.001*
		Type of Task *Tot	0.286	0.000*	0.000*
		Type of Task	0.020*	0.082	0.471
	P_3P_4	ToT	0.000*	0.075	0.445
		Type of Task *Tot	0.041*	0.279	0.391
		Type of Task	0.292	0.766	0.359
	F_ZP_Z	ToT	0.578	0.302	0.494
		Type of Task *Tot	0.508	0.265	0.386
		Type of Task	0.786	0.586	0.733
2	O_1O_2	ToT	0.540	0.106	0.253
		Type of Task *Tot	0.260	0.028*	0.337
		Type of Task	0.815	0.972	0.063
	P_3P_4	ToT	0.449	0.501	0.412
		Type of Task *Tot	0.377	0.350	0.332

Table 3. Electroencephalography RPθ, RPα and RPβ results of the participants based on task WR

Task	Channel location	Factor (s)	RPθ	RPa	RPβ
			p	p	p
		Type of Task	0.755	0.697	0.333
	F_ZP_Z	ToT	0.092	0.053	0.128
		Type of Task *Tot	0.511	0.109	0.105
		Type of Task	0.406	0.796	0.796
1	O_1O_2	ToT	0.342	0.065	0.079
		Type of Task *Tot	0.306	0.046	0.019*
		Type of Task	0.068	0.076	0.466
	P_3P_4	ToT	0.173	0.072	0.883
		Type of Task *Tot	0.237	0.32	0.021*
		Type of Task	0.519	0.442	0.345
	F_ZP_Z	ToT	0.412	0.182	0.000*
		Type of Task *Tot	0.447	0.375	0.092
		Type of Task	0.185	0.21	0.821
2	O_1O_2	ToT	0.454	0.314	0.183
		Type of Task *Tot	0.344	0.568	0.812
		Type of Task	0.562	0.069	0.721
	P_3P_4	ToT	0.411	0.22	0.204
		Type of Task *Tot	0.492	0.483	0.443

For RPθ of channel P3P4 of Task 1 (WoR), there was a significant effect of the type of task ($p = 0.020$). Post-hoc comparisons using the Bonferroni test indicated that the mean RPθ for the Task 1a (M = 4.98, SE = 1.92) was significantly different from the Task 1c (M = 6.78, SE =2.38), p = 0.031. It was found that there was a significant effect of the ToT ($p < 0.001$). There was a significant effect of the interaction between type of task and ToT ($p = 0.041$). For the RPα of channel FZPZ of Task 1 (Without-Rest), there was a significant effect of the ToT ($p < 0.001$). There was a significant effect of the interaction between the type of task and ToT ($p = 0.021$). For the RPα of channel O1O2 of Task 1 (WoR), there was a significant effect of the type of task ($p = 0.049$) and ToT ($p < 0.001$). A significant effect was found of the interaction between type of task and ToT ($p < 0.001$). For the RPα of channel O1O2 of Task 2 (WoR), there was a significant effect of the interaction between type of task and ToT ($p = 0.028$).

For the RPβ of channel FZPZ of Task 1 (WoR), there was a significant effect of the ToT ($p = 0.001$). There was a significant effect of the interaction between type of task and ToT ($p < 0.001$). For the RPβ of channel O1O2 of Task 1 (WoR), there was a significant effect of the type of task ($p = 0.009$). Post-hoc comparisons using the Bonferroni test indicated that the mean RPβ for the Task 1a (M =23.99, SE = 5.24) was significantly different from the Task 1c (M =34.55, SE =2.71), $p = 0.036$. It was found that there was a significant effect of the ToT ($p = 0.001$). There was a significant effect of the interaction between type of task and ToT ($p < 0.001$).

Based on significant effect of the type of task on RPθ and RPβ, the experimental tasks design generated varying degrees of mental workload and a measure of mental fatigue. Task 1a induced less mental workload and mental fatigue levels compared to Task 1c.

For the RPβ of channel O1O2 of Task 1 (WR), there was a significant effect of the interaction between type of task and ToT ($p = 0.019$). For the RPβ of channel P3P4, there was a significant effect of the interaction between type of task and ToT ($p = 0.021$). For the RPβ of channel FZPZ of Task 2, there was a significant effect of the ToT ($p < 0.001$).

A comparison was made on EEG frequencies in Task 1a which was conducted once in WoR segment and twice in WR segment (at the beginning and end of the segment). The results of repeated measure ANOVA with type of conditions (three conditions; WoR Segment, Beginning of WR Segment and End of WR Segment) are reported in Table 4.

Table 4. Results of repeated measure ANOVA ON Task 1a in three conditions

Frequency ($\mu v^2/Hz$)	Channel location	*p*
RPθ	F_ZP_Z	0.187
	O_1O_2	0.089
	P_3P_4	0.867
RPα	F_ZP_Z	0.613
	O_1O_2	0.545
	P_3P_4	0.007**
RPβ	F_ZP_Z	0.622
	O_1O_2	0.114
	P_3P_4	0.013*

For RPα of channel P3P4, (Fig. 6) there was a significant effect of the type of condition ($p = 0.003$). The mean RPα for the WoR Segment (M = 2.71, SE = 1.02) was substantially different from the End of WR Segment (M = 10.68, SE =1.34), $p = 0.017$. It was discovered that the situation had a substantial effect on the RPβ of channel P3P4 ($p = 0.013$) (Fig. 7).

However, by employing the Bonferroni test, post-hoc analyses revealed no statistically significant differences across overall conditions ($p > 0.05$). Fig.s 7 and 8 present the significant EEG frequencies tabulations along the two types of the condition

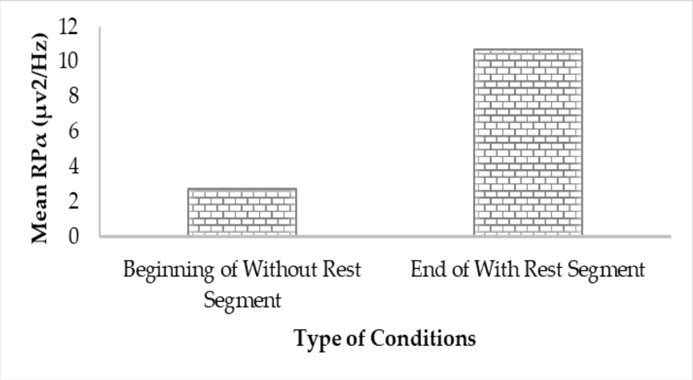

Fig. 6. Mean RPα of channel P3P4 in different the type of conditions

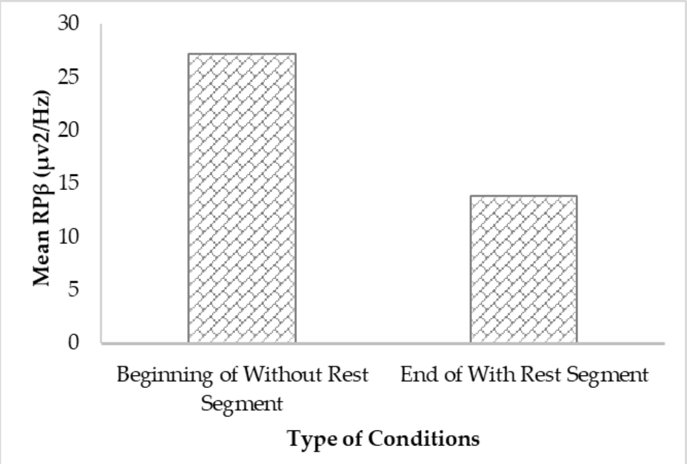

Fig. 7. Mean RPβ of channel P3P4 in different the type of conditions

3.2 Heart rate based on tasks and experimental segments

The results of the 2×2 repeated measure 1a, Task 1b and Task 1c) and time on task (ToT) (M1 to M20) as within subject factors for Heart rate of both segments are presented in this section. The results of the 2×2 repeated measure ANOVA with the type of task (two types; Task 2a and Task 2b) and time on task (ToT) (M1 to M30) as within subject factors for Heart rate are reported in Table 5.

Table 5. Heart rate results of the participants based on task WoR and WR

Task	Factor (s)	WoR	WR
		p	*p*
1	Type of Task	0.206	0.128
	ToT	0.063	0.000**
	Type of Task *Tot	0.002**	0.000**
2	Type of Task	0.0268	0.716
	ToT	0.0328	0.003**
	Type of Task *Tot	0.031*	0.006**

For Heart rate of Task 1 (WoR), there was a significant effect of the interaction between type of task and ToT ($p = 0.002$). For Heart rate of Task 2 (WoR), there was a significant effect of the interaction between the type of task and ToT ($p = 0.031$). For Heart rate of Task 1 (WR), it was found that there was a significant effect of the ToT ($p < 0.001$). For Heart rate of Task 2 (WR), it was found that there was a significant effect of the ToT ($p = 0.003$). In addition, it was found that there was a significant effect of the interaction between type of task and ToT ($p = 0.006$).

An independent sample t-test was conducted to compare the mean Heart rate in WoR and WR segment for each task and the results are presented in Table 6. It is evident that there were statistically significant differences found in all tasks ($p < 0.05$). This shows that there are significant differences found in Heart rate in all tasks comparing between WoR and WR segment.

Table 6. Comparison of mean Heart rate between WoR and WR experimental segment

Type of task	WoR		WR		*t*	*p*
	Mean	SD	Mean	SD		
Task 1a	79.61	1.18	70.37	0.84	28.625	0.000*
Task 1b	78.31	1.28	69.40	1.35	21.399	0.000*
Task 1c	79.74	1.21	69.29	1.36	25.710	0.000*
Task 2a	77.23	1.69	68.24	2.24	17.535	0.000*
Task 2b	75.59	1.82	68.46	1.69	15.748	0.000*

The results of the mean Heart rate of the participants along the tasks are presented in Fig. 8. The mean Heart rate for Task 1c in WoR segment recorded was the highest compared to others. In addition, the results also indicate that the mean Heart rate in WoR tasks was 10 to 14% higher compared to WR tasks.

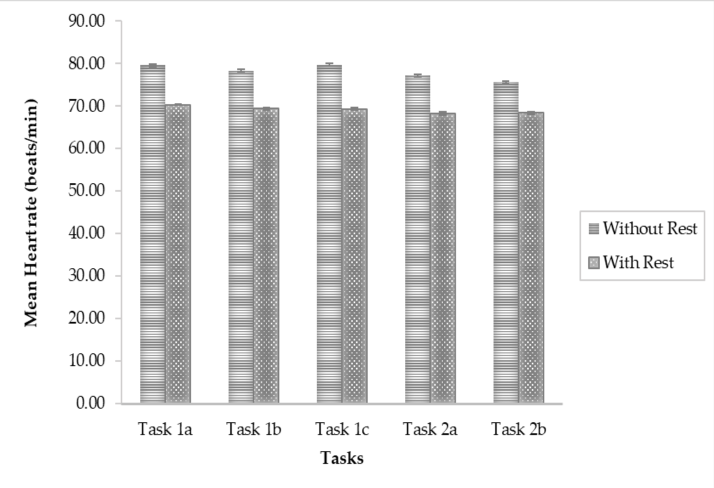

Fig. 8. Mean Heart rate in WoR and WR segment for each task

3.3 Task performance measures

Task performance is represented by the mean score of the tasks of each participant (Fig. 9). Using a mixed model repeated measures ANOVA, for Task 1 of WoR segment, it was found that there was no significant effect of the type of task on the task performance score ($F(1,10) = 0.807$, $p > 0.05$). For Task 2, there was no significant effect of the type of task found on the task performance score ($F(1,4) = 6.793$, $p > 0.05$).

Meanwhile, for Task 1 of WR segment, there was a significant effect of the type of task on the task performance score ($F(1,4) = 6.203$, $p = 0.024$). For Task 2, there was no significant effect of the type of task found on the task performance score ($F(1,9) = 2.516$, $p > 0.05$).

An independent samples t-test was conducted to compare the mean task performance score in WoR and WR segment for each task and the results are presented in Table 7. No statistically significant difference found in all tasks ($p > 0.05$). This shows that there is no significant difference in Task performance score of WoR and WR segment.

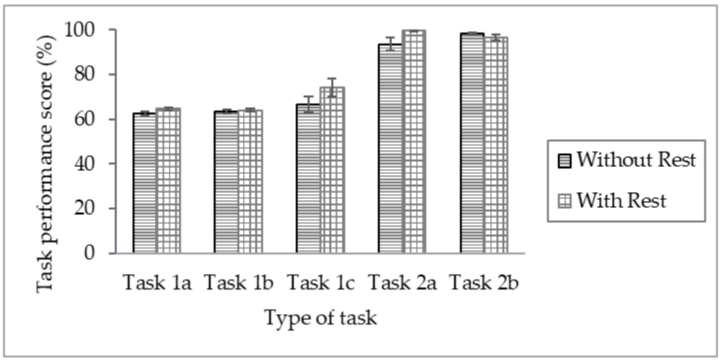

Fig. 9. Mean of Task performance score

Table 7. Comparison of Task performance score between WoR and WR experimental segment

Type of task	WoR		WR		*t*	*p*
	Mean	SD	Mean	SD		
Task 1a	62.45	2.85	64.72	1.65	-1.634	0.126
Task 1b	63.46	2.78	64.15	1.53	-0.514	0.616
Task 1c	66.58	11.60	74.42	9.02	-1.316	0.211
Task 2a	93.64	8.86	99.54	0.62	-2.095	0.065
Task 2b	98.32	1.70	96.58	2.95	1.469	0.166

3.4 Relationship between mental workload and mental fatigue measures

To quantify the association between mental workload and mental fatigue measurements in the WoR segment, correlation and regression analyses were used. This study created seven mental workload and mental fatigue conceptual models to evaluate the variability of both parts of two types of activities, namely, data entry and arithmetic tasks. The models are based on the electrode placements (channel locations), with Fz and Pz providing information on intentional and motivational behavior; locations near P3 and P4 contributing to perception and differentiation activity; and area O1 and O2 providing output on an individual's primary visual [6, 37].

RPα and RPβ present the mental workload, while RPθ presents the mental fatigue. The models were created on the assumption that different types of tasks will result in varying mental workloads, which will alter the pattern of mental fatigue. Based on previous research, it was discovered that different types of tasks result in varied levels of mental workload and mental fatigue, therefore, models were created individually for data input, arithmetic, and a combination of the two.

3.4.1 Data entry task

The experimental results demonstrated that mental fatigue (RPθ) and mental workload (RPα) of channel location FzPz ($r = 0.746$, $p = 0.013$) had significant correlations. There were strong connections between mental fatigue (RPθ) and mental workload (RP: $r = 0.744$, $p = 0.014$ and RP: $r = 0.861$, $p = 0.001$) for channel location O1O2. There were strong connections between mental fatigue (RPθ) and mental workload (RPα) for channel location P3P4 ($r = 0.885$, $p < 0.001$). These variables have strong relationships with R-values above 0.5.

For intentional and motivational brain location (FZPZ), a significant regression equation was found ($F(1, 8) = 10.05$, $p = 0.013$), with an adjusted R^2 of 0.501. Thus, the prediction model:

$$Y = -1.532 + 1.787\,(X1)$$

Where Y = Mental fatigue; X1 = RPα

For primary visual brain location (O1O2), a significant regression equation was found (F (2, 7) = 11.26, p = 0.006), with an adjusted R^2 of 0.695. Thus, the prediction model:

$$Y = 6.278 – 0.184 (X1) + 0.204 (X2)$$

Where Y = Mental fatigue; X1 = RPα, X2 = RPβ

For perception and differentiation brain location (P3P4), a significant regression equation was found (F (1, 8) = 28.84, p = 0.001), with an adjusted R^2 of 0.756. Thus, the prediction model:

$$Y = 0.611 + 0.967 (X1)$$

Where Y = Mental fatigue; X1 = RPβ

3.4.2 Arithmetic task

The experimental results revealed that there were significant correlations between mental fatigue (RPθ) and mental workload (RPα) of channel location FzPz (r = 0.843, p = 0.002). For channel location P3P4, there were significant correlations between mental fatigue (RPθ) and mental workload (RPα) (r = 0.944, p = 0.001). Strong correlations were found for these factors where R-value is above 0.5.

For intentional and motivational brain location (FzPz), a significant regression equation was found (F (1, 8) = 19.67, p = 0.002), with an adjusted R^2 of 0.675. Thus, the prediction model:

$$Y = -0.687 + 1.951 (X1)$$

Where Y = Mental fatigue; X1 = RPα

For perception and differentiation brain location (P3P4), a significant regression equation was found (F (1, 5) = 40.69, p = 0.001), with an adjusted R^2 of 0.869. Thus, the prediction model:

$$Y = 0.552 + 0.927 (X1)$$

Where Y = Mental fatigue; X1 = RPα

3.4.3 Combination of both data entry and arithmetic task

The experimental results revealed that there were significant correlations between mental fatigue (RPθ) and mental workload (RPα) of channel location FzPz (r = 0.809, p = 0.002). For channel location P3P4, there were significant correlations between mental fatigue (RPθ) and mental workload (RPα) (r = 0.951, p = 0.001). Strong correlations were found for these factors where R-value is above 0.5.

For intentional and motivational brain location (FzPz), a significant regression equation was found (F (1, 8) = 15.19, p = 0.005), with an adjusted R^2 of 0.612. Thus, the prediction model:

$$Y = -2.346 + 2.015 (X1)$$

Where Y = Mental fatigue; X1 = RPα

For perception and differentiation brain location (P3P4), a significant regression equation was found (F (1, 5) = 46.84, p = 0.001), with an adjusted R^2 of 0.884. Thus, the prediction model:

$$Y = -0.311 + 0.984 (X1)$$

Where Y = Mental fatigue; X1 = RPα

The results highlighted three regression models for data entry tasks, two regression models for arithmetic tasks and two regression models for the combination of the tasks. These seven models can be used to predict mental workload and mental fatigue further to design the works. The validity of each proposed models is very high with the highest R^2 of 0.884 for the combination of both tasks, and of 0.869 for the arithmetic task. The models indicated that mental workload measures associated to mental fatigue can be either represented by one or more variables in a model depending on the tasks performed.

4 Discussion.

This study discovered trends of mental workload and mental fatigue measured by physiological procedures based on computer task assigned to the participants. For the WoR, it was found that copying text task based on provided format (data entry) significantly induced lower sleepiness and drowsiness compared to other tasks reflected by lower theta and alpha signal during the task execution. These signals showed obvious significant differences in location indicating intention (frontal) and visualization (occipital) [37]. The findings coincide with a previous study that theta and alpha are more accurate reflection of the mental workload and mental fatigue [3, 38-40]. These results are consistent with previous studies highlighting the increment of sleepiness and information processing [6, 41].

Mental fatigue is observed as a decreased efficiency reflected by attention degradation, and could have effects on elective attention and awakens [42]. The findings are similar with that of previous research, which demonstrated that alpha power shows load variations [43, 44]. Based on the comparison made, the finding reflects that the copying task requires lower effort as it can be considered as simple and prearranged task while it was obvious that replying email induced higher cognitive load as they need to utilize their visual attention, memory, information processing and decision making on the content of the email. This finding is consistent with study by Chen et al., [45] which stated that their planned tasks induced lower mental workload compared to altered tasks that requires more information processing.

As for the WR segment, it was found that alertness is different in tasks assigned especially in copying text task are depending on time of task. This study is parallel with findings by Barrouillet et al.,[46] that time-based function of working memory in which processing and storage rely on a single and general purpose attentional resource needed to run executive processes. Significant difference was found when comparing signals in copying text task which was conducted in WoR and WR segment. Further analysis indicated that alpha signal was significantly higher at the end of WR Segment compared to WoR segment. This finding reflected that the participants experienced more relaxed and complacent during the task with given rests time thus less prone to mental overloaded and fatigue. These findings are consistent with previous findings that alpha waves arise during relaxed, conditions, and in a drowsy but wakeful state [47].

As a measure of brain state and its dynamics, the signals output can be considered corresponding to the heartbeat, an indicator of the cardiovascular state [48] and valid representation as a workload index [49]. In this study, the HR is measured during the experiment as part of physiological measures. HR is believed to reflect the heart's ability to adapt to changing circumstances by detecting and quickly responding to unpredictable stimuli. The findings of the analysis agreed with previous studies that HR analysis is able to assess overall cardiac condition and the state of the autonomic nervous system responsible for regulating cardiac activity [50].

From the tasks assigned in both WoR and WR session, the earliest duration of the data entry task (copying and typing text tasks) significantly induced lower HR compared to the remaining duration of the tasks. This finding shows that the participants might had the initial understanding that the task required minimal effort. However, for typing text from books task, the HR significantly high after two minutes of working duration compared to the remaining minutes especially towards the end. These significant differences may be due to challenges found from the task and reflecting increasing workload [8], but the participants may familiarize and adopted some strategies later to execute the task assigned.

An interesting trend was found from tasks involving numbers (budget preparation) where HR was found lower during the simple budget task execution compared to difficult budget task execution. This finding is parallel with study by Gao et al., [51] that cardiac measures were able to distinguish tasks with different overall complexity. Comparison of HR between WoR and WR segment for each task show that HR of WR tasks were significantly lower in all tasks. These findings highlighted the importance of rest between computer tasks. As mental workload increased with task duration and can induce computer vision syndrome [52], it is recommended that appropriate rest-time intervals must be considered to ensure optimum mental workload and consequently high productivity [53].

Task performance is based on the mean score of the tasks executed. Although the results indicated slight significant effects of the type of task, the task performance of replying email was higher than the copying and typing text tasks. These findings indicate that the participants are prone to have higher overall performance on task that required active visual attention, memory, information processing and decision making compared to more monotonous tasks. The results shows that monotonous tasks may induce underloaded condition where it may lead to inadequate activation and scarce use of individuals' available resources, thus the work performance may be negatively affected [54, 55]. These results are concordant with those presented by Jackson et al., [56] on executive control, short-term memory, metacognitive monitoring and decision making, pointing out that both under- and overload could lead to poorer performance[57].

This study developed seven mental workload and mental fatigue conceptual models to evaluate the variability of both parts of two types of activities, namely, data entry and arithmetic tasks. The models were constructed using strong correlations between the frequency of brain signals [39, 58].

These findings are consistent with that of earlier research, which suggested a connection between mental workload and fatigue [3, 59]. The brain frequencies offer information on sleepiness and tiredness, which reflect the induction of mental fatigue elements, whereas alertness and information processing describe the state of mental workload in performing the assigned computer activities. Hence the ability to predict mental workload and mental fatigue for computer works from brain frequencies was established.

These models will be useful to design solutions that integrate human factors, safety, and health elements in the work system productivity. Several recommendations can be used to design work performance support features for workers based on the findings. It was stated that implementing work-rest reduces the risk of workers feeling overworked and mentally exhausted. From the findings, it is recommended that workers take short breaks to increase alertness by reducing monotonous tasks and allowing mental break and moderate levels of physical activity. These findings will be highly advantageous for organizations to plan and manage their resources by optimizing mental workload condition and minimizing mental fatigue occurrence. The main findings are summarized in Table 8.

Table 8: Summary of findings and discussions

No.	Current study	Consistent or Opposite	Previous studies
1.	• Copying text task induced lower sleepiness and drowsiness reflected by lower theta and alpha signal during the task execution.	Consistent	• Theta and alpha are more accurate reflection of the mental workload and mental fatigue [3, 38-40].
2.	• Copying task requires lower effort and considered as simple and prearranged task while it was obvious that replying email induced higher cognitive load.	Consistent	• Planned tasks induced lower mental workload compared to altered tasks that requires more information processing [45].
3.	• Alertness level is different in tasks assigned especially in copying text task are depending on time of task.	Consistent	• Time-based function of working memory in which processing and storage rely on a single and general purpose attentional resource needed to run executive processes[46].
4.	• Alpha signal was significantly higher at the end of WR segment compared to WoR segment.	Consistent	• The alpha waves arise during relaxed, conditions, and in a drowsy but wakeful state [47].
5.	• HR was found lower during the simple budget task execution compared to difficult budget task execution.	Consistent	• Cardiac measures were able to distinguish tasks with different overall complexity [51].
6.	• Monotonous tasks may induce underloaded condition.	Consistent	• Both under- and overload could lead to poorer performance [56,57].
7.	• This study developed seven mental workload and mental fatigue conceptual models to evaluate the variability of both parts of two types of activities, namely, data entry and arithmetic tasks.	Consistent	• Suggested a connection between mental workload and fatigue [3, 59].

5 Conclusion.

This study has identified significant trends and relationship between mental workload and mental fatigue level among service sector workers. Secondly, this study constructed mental workload and mental fatigue level models based on multi-channel EEG relative power bands. For both the data input and arithmetic tasks, there were high relationships between mental workload and mental fatigue measurements. The proposed models achieved indicated a new method to determine the mental fatigue of service sector workers. They are expected to provide a reference value of worker's condition by giving physiological signals. This research makes various significant contributions, particularly in the fields of human factors and ergonomics. This research has created a novel method for determining mental fatigue based on mental workload measurements. The systematically validated strategy entails assessing real-time task and physiological parameters. Organizations can use this strategy to improve and maintain worker performance while reducing the risk of errors and accidents caused by excessive mental workload and mental fatigue.

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