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RESEARCH ARTICLE

An Assessment of Researchers' Mental Workload and Fatigue While Engaged in Research Using Machine Learning and NASA-TLX

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Abstract

Objectives: This research aims to identify the prime predictors of researchers' cognitive fatigue and mental workload while engaged in research endeavors using Binary Logistic Regression and NASA-TLX. **Methods:** The Mental Fatigue level and workload of seventy-nine researchers were assessed using the Samn-Perelli Fatigue Scale and NASA-TLX on a two-month survey. Then, the prime predictors of Fatigue were identified using binary logistics regression, and the significant differences among NASA-TLX mental workload dimensions were detected at different work shifts and time points through paired sample t-tests. **Findings:** Paired sample t-test reveals a significant difference between before and after research work mental fatigue scores ($p<0.001$) as well as baseline fatigue between morning and afternoon ($p<0.000$). The p-values for baseline fatigue, the shift being worked (morning or afternoon), and the average NASA-TLX score are less than 0.05 in the binary logistic regression, which makes them the three main predictors of mental fatigue in research work. The mean score for 'Mental demand' was 80, the highest NASA-TLX dimension, which shows a significant difference with all other dimensions except 'effort.' Therefore, these two dimensions contribute the most to mental fatigue. Overall, researchers can reduce their mental fatigue by avoiding working the afternoon shift, managing their mental demands and effort effectively, and not engaging in the research work while feeling tired. **Novelty:** Employing the NASA-TLX combined with the binary logistic regression model, which can predict the primary predictors of mental fatigue and cognitive workload experienced by researchers and scholars.

Keywords: NASA-TLX; ML; Mental Fatigue; Binary Logistic Regression; Cognitive Ergonomics

1 Introduction

Research work involves the systematic pursuit of knowledge through study, analysis, and experimentation to address academic, scientific, or societal questions[1]. These activities can generate a Mental workload, which refers to the cognitive demands and effort required to manage tasks such as data analysis, writing, or problem-solving[2]. In these sets of tasks, there occurs a decline in focus, efficiency, and decision-making ability, known as cognitive fatigue, due to prolonged intellectual exertion or stress during scholarly activities[3]. The thinking required for carrying out fruitful research starts from a literature survey, experimental design, data collection, analysis, and interpretation, which can put the researchers under mental strain for an extended period. If cognitive workload builds up and needs to be appropriately resolved, critical skills like problem-solving, memory, and focus diminish, ultimately impacting the research quality[4]. The workload can also cause burnout and errors, which makes workload management for researchers more critical. Therefore, maintaining and reducing cognitive workload is crucial to the researchers as these factors determine effectiveness and efficiency, innovative brainstorming, and the reliability of the findings[5]. Additionally, effective workload management can enhance sustained engagement and well-being, reducing the risks of burnout and errors.

Therefore, finding out the primary predictors of high cognitive workload and mental fatigue in research work is essential to manage and reduce researchers' mental fatigue and workload. Measures can be taken by institutions and organizations based on critical predictors like time pressure and mental demand and working in ineffective times to reduce stress. Knowledge of these factors can be helpful in the organization of work environment, conditions, and shift schedules that enable scholars to persist at their best performance for long periods without adverse effects on their health[6]. For example, adopting effective time management and shift breaks could significantly alleviate the stress of a researcher[7].

Well-known tools for measuring cognitive workload and mental fatigue in the manufacturing and service sector include NASA-TLX and the Samn-Perelli Fatigue Scale[8]. In NASA TLX, users' ratings against workload dimensions like mental demand, temporal demand, and effort can capture a complete workload profile[9]. Samn-Perelli Fatigue Scale is a rating-based seven-point scale that captures a person's fatigue[10]. Several recent studies have used these tools to assess manufacturing sector workers' and service professionals' workload and mental fatigue[11]. However, a few research gaps exist in the existing literature, as follows:

i. NASA-TLX and the Samn-Perelli Fatigue Scale are, to the best of the author's knowledge, not used to assess the mental fatigue and cognitive workload of researchers.

ii. Although the machine learning-based approach to research is increasingly used, a limited number of studies utilize it for mental fatigue and workload assessment.

To address these gaps, this study aims to:

i. Identify the primary predictors of researchers' cognitive workload and mental fatigue using Binary Logistics Regression.

ii. Find out the work shift for scholars, which makes them more fatigued and generates a high cognitive workload.

iii. Which dimensions of NASA-TLX are the most significant in generating a high cognitive workload.

The authors use a self-assessment questionnaire called the Samn-Perelli Fatigue Scale to capture the data on mental fatigue. This scale determines one's level of fatigue or how tired one is from the inside out. On the other hand, Binary Logistic Regression is highly effective for investigating possible predictors of binary categorical target variables like mental fatigue because it deals with the probability of fatigue by estimating it through predictor variables, giving a precise mean of identifying possible factors[(12)]. NASA-TLX and Samn-Perelli Fatigue Scale are better because they present subtle categories of cognitive workload and finer subjective fatigue levels, paralleling their assessments to those of real-life scenarios[(13)].

2 Methodology

This study utilizes the NASA-TLX and Same-Perelli Fatigue Scale to collect data on researchers' cognitive workload and mental fatigue. Then, the rating data was classified into high and low fatigue ones. Next, binary logistics regression using IBM SPSS 25 was carried out to determine the main predictors of high fatigue among researchers. Further, this research carried out several paired sample t-tests on SPSS to detect the significant difference between the fatigue of different work shifts and the significant dimensions of NASA-TLX, which contribute to high fatigue.

2.1 Participants

Prior to collecting data and carrying out the research, the authors applied for ethical approval to the ethical review committee at Jashore University of Science and Technology. They obtained the ethical approval on 09th March 2024, having the reference ERC/FBST/JUST/2024-191. This approval allows the authors to collect the researchers' survey data as that survey does not harm any human, and no clinical sample, like a blood sample, is required. In this study, seventy-nine researchers from different institutions and organizations (mostly faculty members of universities) participated in complex research activities. Most participants were male, accounting for almost 85% of the total, while the remaining 15% were female. On average, the participants were 32.37 years old, with a standard deviation of 5.26, and they possessed an average of 6.5 years of research experience, with a standard deviation of 3.79. A significant portion of the participants (65%) were seasoned researchers with more than 5 years of experience and were 32 years or older. A small percentage of participants (5%) had less than two years of research experience. It is worth noting that all researchers, regardless of their gender, were given an equal opportunity to take part in the study, ensuring a diverse and inclusive sample for the research on mental workload and fatigue during complex research activities. In this survey, 52% -41 participants- of the data was collected in the morning shift, and the rest, 48% -38 participants were collected in the afternoon or evening shift. The confounding factors like individual variations in workload tolerance and energy level variation on different days are controlled by taking data on multiple days and multiple time points, and the mode of the data has been taken into consideration. Thus, the individual factors and other confounding factors were controlled.

2.2 Procedure

Data collection spanned two months, during which researchers were deeply immersed in various research tasks and activities. To quantify their fatigue levels, researchers rigorously assessed themselves twice during each day - at the beginning and end - through the Samn-Perelli Fatigue Scale. Furthermore, workload assessments were completed after each shift using the NASA-TLX method[(14)]. In addition to fatigue and workload assessments, researchers reported their sleep duration and previous meals, offering a comprehensive view of their well-being and work patterns. This meticulous data collection approach thoroughly examined the factors influencing researchers' mental workload and fatigue levels while engaging in complex research activities.

2.3 Evaluation of Fatigue

The authors used a Google form-based survey to assess their fatigue levels before and after each work shift. The survey used a 7-point scale, with 1 being "fully alert, wide awake" and 7 being "completely exhausted, unable to perform efficiently." Table 1 summarizes the 7-point scale.

Table 1. Description of Samn & Perelli fatigue scale

Score Point	Description
1	Completely alert, fully awake
2	Lively, responsive, but not fully
3	Okay, almost fresh
4	Little bit tired, somewhat less fresh
5	Middling fatigued, let down

Continued on next page

Table 1 continued

6	Highly tired, concentration is extremely difficult
7	Fully Exhausted, unable to carry out task efficiently

The Samn & Perelli fatigue scale (SPFS) was chosen for its simplicity. Being a single-dimensional scale, the SPFS allows for easy and frequent use in field settings, and it can be seamlessly integrated with other subjective assessment methods. Additionally, the SPFS is utilized in numerous studies examining self-reported (survey-based) tiredness levels among railway workers, aircraft deicing technicians, and commercial and military pilots [15]. The scale is sensitive to changes in tiredness levels during the workday and has shown strong trustworthiness in several testing scenarios. The scale developers also identified four fatigue categories and their anticipated impacts on performance, with Category 1 and Category 2 indicating significant declines in performance (Table 2).

Table 2. Fatigue Categories and Expected Impact on Performance

Category	Scores	Fatigue Impact on Performance
4	1-3	Fully Alert: Performance is not Impaired by Fatigue
3	4	Fatigue: Performance is Impaired but is not Considered Significant.
2	5-6	Middling to Severe Fatigue: Likely Experience of Performance Impairment
1	7	Extreme Fatigue: Performance Clearly Affected.

The score 5, which is the lower limit of Category 2, is regarded as a crucial threshold because of its importance in civilian aviation. In this study, "high fatigue" was defined as exhaustion levels that were considered high enough to impair performance (moderate to severe fatigue level where fatigue score is greater than or equal to 5). As a result, the SPFS value of 5 was a crucial cutoff point for classifying low and high fatigue levels in statistical analysis [16].

2.4 Cognitive Workload Evaluation

Workload was measured against six dimensions of the NASA-TLX method [17]. This approach has been validated and routinely used to measure subjective workload [18]. The NASA-TLX analyses cognitive workload in six aspects, three of which quantify mental demand, physical demand, and temporal demand. The remaining three criteria rate work performance, effort, and perceived frustration. Either dimension is represented by a 20-point scale with labels ranging from 'Low' to 'High' or 'Good' to 'Poor' at either end. In this study, a score ranging from 0 to 100, which is rounded to the closest 5 was acquired for each of the six dimensions, which were then averaged to provide a single NASA-TLX average score. In this study, the average NASA-TLX score was employed as a predictor in binary logistic regression because the combined score has been scrutinized in previous publications [19,20].

2.5 Statistical Analysis

The key dependent variable of interest was fatigue levels, measured using interval rating scales. Central tendency and dispersion measurements were taken as means and standard deviations. Paired-sample t-tests (also known as dependent sample t-tests) were used to compare data from the same population, such as tiredness levels before and after shifts. Noteworthy studies have used machine learning methods to study cognitive workload [21]. Therefore, binary logistic regression was used to identify predictors of high fatigue (defined as reporting a fatigue level of 5 or above on the Samn-Perelli fatigue scale). Numerous studies have proved the resilience of parametric t-tests, even when using ordinal data or when sample size and normality requirements are violated. Furthermore, past research has used parametric statistics, such as ANOVA and t-tests, in conjunction with both the NASA-TLX as well as Samn-Perelli Fatigue Scale. A significance level 0.05 was selected for inference tests, consistent with the standard threshold in scientific research. All the statistical analysis and the binary logistics regression were carried out on the IBM SPSS 25.

3 Results and Discussion

3.1 Exploratory Analysis and t-test

Among the 79 participants in the study, the average reported sleep duration was 6.49 hours, ranging from a minimum of 3 hours to a maximum of 10 hours, with a standard deviation of 1.79. This information offers significant insights into the sleep habits of researchers involved in intricate research tasks. A more detailed analysis, in Figure 1, of the sleep duration distribution reveals that a significant proportion of participants reported sleeping less than the recommended seven hours for optimal health and performance, as suggested by scientific consensus. Specifically, 54.4% of participants reported sleeping less than seven hours, highlighting insufficient sleep among the research cohort. Furthermore, 27.8% of participants reported sleeping six hours or less, indicating a substantial portion of the group experiencing even more pronounced sleep deficits (Figure 1). These findings underscore the importance of considering sleep duration as a critical factor in understanding researchers' well-being and performance during demanding research tasks.

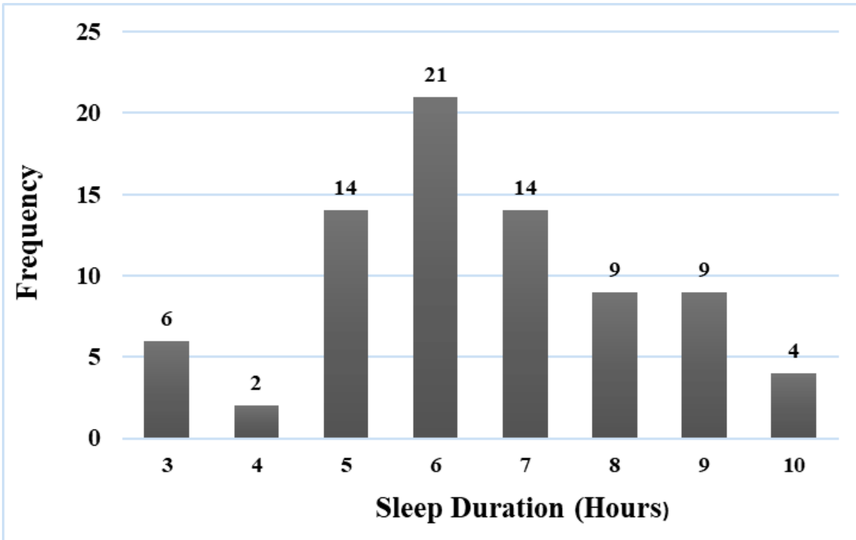

Fig 1. The distribution of reported sleep duration

Another key aspect of studying the well-being of the researchers is the fatigue score. The average fatigue score perceived by the researchers notably rose from 2.80 before commencing a research shift to 4.85 by the end, indicating a probable impact of research activities on fatigue levels. Figures 2 and 3 illustrate the distributions of combined (morning and evening) fatigue scores before and after research activities. However, more than 25% of the participants reported a fatigue 7 on the SPFS scale after the shift. This observed escalation in fatigue scores suggests a direct impact of the demanding research work on the researchers' fatigue levels, highlighting the taxing nature of their tasks and the potential strain experienced during the research process. The mean fatigue level identified in our study exceeds those documented for railway workers in Australia (mean: 4.0, SD: 1.3), aircraft technicians (mean: 4.1, SD: 1.0), and in their investigation of fatigue among airline pilots[22]. It is worth noting that mean fatigue ratings may not accurately depict actual risk, as emphasized by the Civil Aviation Authority in the UK.

In analyzing the participants' reported fatigue levels before commencing their research work, it is noteworthy that none indicated extreme fatigue, corresponding to a seven on the SPFS scale. A paired sample t-test revealed a significant difference between the fatigue before and after a research shift, as demonstrated in Table 3. The significant difference in before and after fatigue scores in the shift underlines the intensity and challenges the researchers face while engaging in complex research activities. This shift in fatigue may reflect the cumulative effect of prolonged cognitive engagement, problem-solving, and concentration required during the research tasks.

Table 3. Summary of the outcomes of inferential statistical analysis employing t-tests

Variable	Factor	Participants	Mean	SD	*p -value*
Fatigue	Before work	79	2.80	1.53	*≤ 0.001*
	After work	79	4.85	1.67	
Fatigue	Before morning work	38	3.89	1.110	*≤ 0.000*
	Before evening work	38	1.76	1.125	

Italicized values denote statistical significance (p-value $\leq$ 0.05)

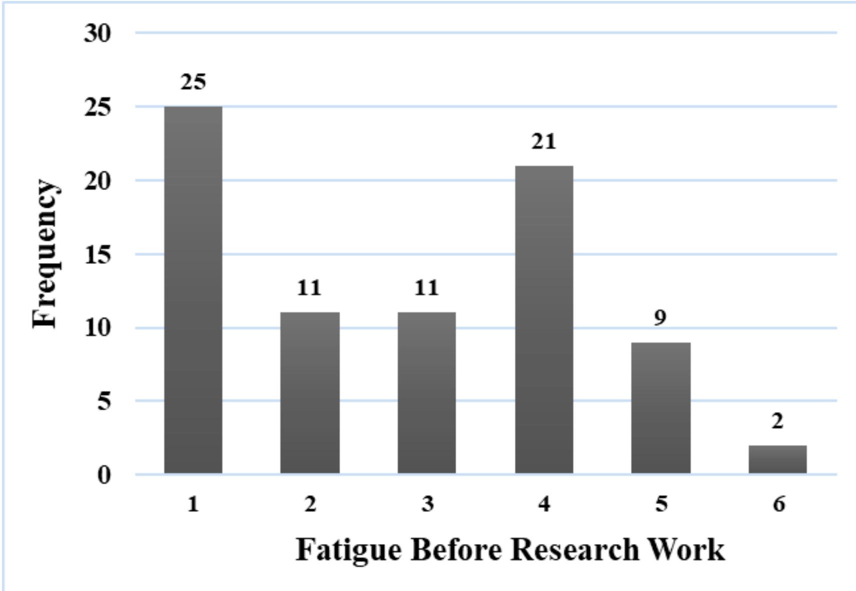

Fig 2. The distributions of combine (morning and evening) fatigue scores before research work

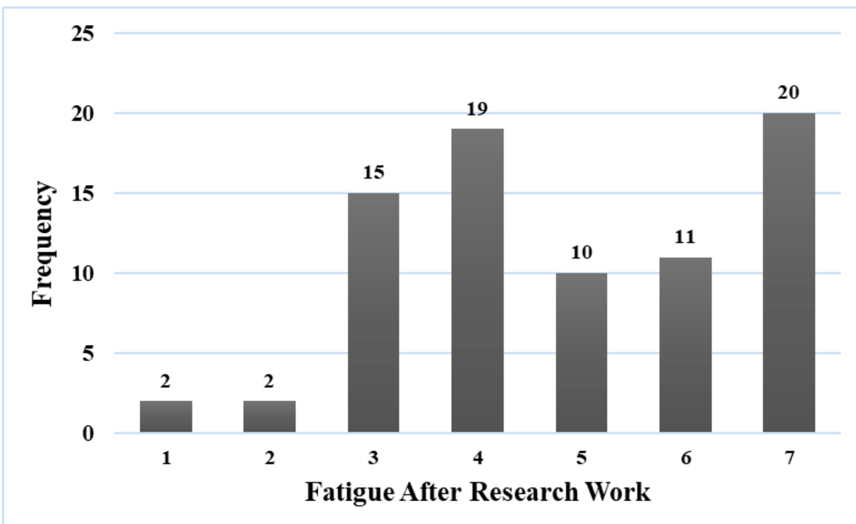

Fig 3. The distributions of combine (morning and evening) fatigue scores after research work

Comparing baseline fatigue levels before morning and evening work revealed a significant difference—through a paired sample t-test—in the researchers' fatigue experiences at different times of the day (Table 3). The distinct difference in fatigue levels before morning and evening work suggests that researchers may face varying mental and physical exhaustion levels depending on the time of day.

3.2 Binary Logistics Regression

To further analyze and detect the key factors that contribute to the high fatigue in the scholarly work, Binary logistic regression analysis was carried out. It considers longitudinal data with the dependent variable indicating a fatigue score of 5 or higher (yes/no) and revealed that fatigue before starting a research shift, conducting research in the afternoon or evening, and average NASA-TLX score were prime predictors of elevated fatigue levels at the end of a shift (p-value ≤ 0.05). Here, the average NASA-TLX score was used as a predictor since the combined score has been subject to scrutiny in recent days[23,24].

Table 4. The outcomes of binary logistic regression for the primary variables under study

Variable	Coef.	Odds ratio	95% CI		*p* -value
			Lower	Upper	
Sleep duration	0.154	1.167	0.695	1.960	0.554
Baseline Fatigue	1.199	3.318	1.600	6.877	*0.001*
Meal	-0.829	0.436	0.066	2.897	0.391
Afternoon or Evening shift	-1.976	0.139	0.024	0.794	*0.027*
Average NASA-TLX score	0.082	1.086	1.003	1.175	*0.043*

Italicized values denote statistical significance (p-value $\leq$ 0.05)

This supervised learning model accurately predicted 89.9% of the observations. Additionally, Nagelkerke's R^2, which is a statistic that measures the proportion of variation explained by a binary logistic regression model, value of the model was 0.707; thus, it was accepted. Nagelkerke's R^2 ranges from 0 to 1, with higher values indicating better model fit, and values above 0.5 are generally considered acceptable. This is considered a good fit, implying that the model is able to explain a substantial amount of the variation in the binary outcome. The summary of binary logistic regression is shown in Table 4. Sleep duration and meal intake did not emerge as significant predictors. Notably, the odds ratio for fatigue before starting a research shift as a prime predictor of elevated fatigue levels was notably high at 3.15 compared to other predictors.

3.3 NASA-TLX Dimensions for Mental Workload

Figure 4 depicts the scores against each of the six dimensions of NASA-TLX as box plots, as reported by scholars. 'Mental demand' occupied the top position with the highest mean value of 78.35 out of the six measures, with a standard deviation 14.20. The difference between the highest-scored dimension, mental demand, and other dimensions was significant except for one dimension, effort. Therefore, these two dimensions are the most significant for the researchers' mental workload.

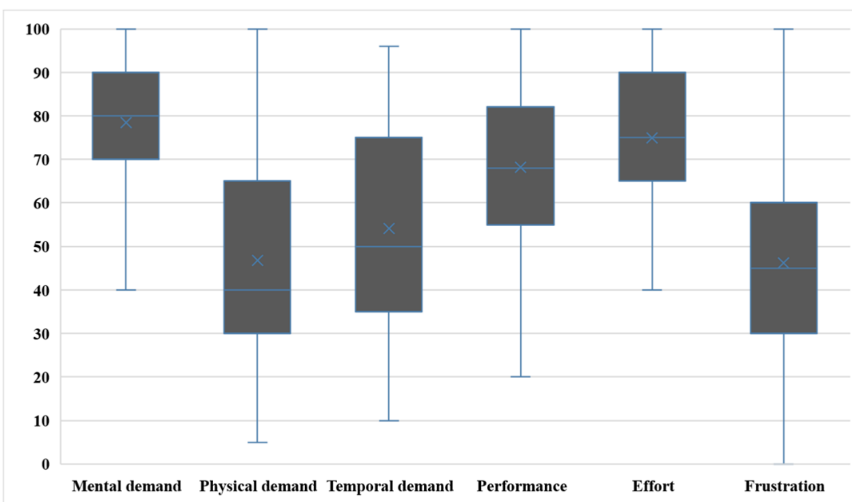

Fig 4. Six components of the NASA-TLX as assessed by researchers

When the dimensions of the NASA-TLX were compared based on the morning and afternoon or evening shifts, none but the frustration showed a statistically significant difference. Thus, frustration is the single dimension that increases significantly when shifts differ, i.e., on the evening shift. Biological mechanisms like homeostasis and circadian rhythms, often known as the "body clock," could also play a role in increased reported fatigue levels[25].

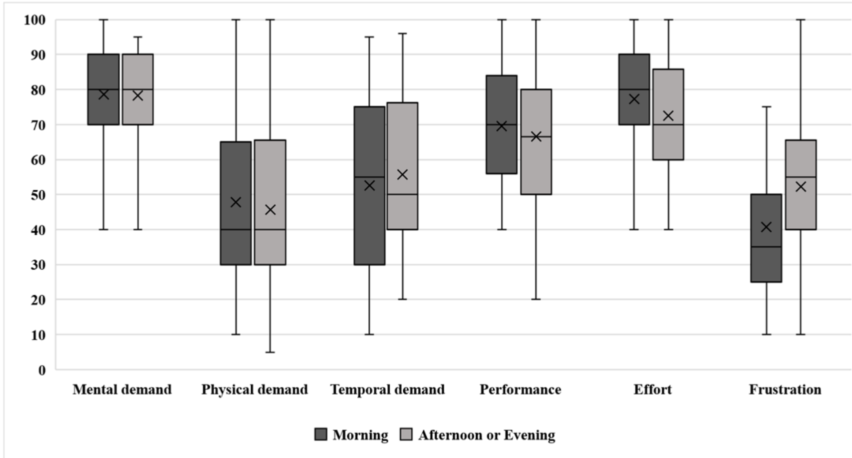

Fig 5. Six components of the NASA-TLX categorized by shift type

3.4 Discussion

Key Findings on Fatigue and its Predictors:

High Fatigue Prevalent: Over half (51.9%) of researchers reported fatigue levels on the SPFS scale exceeding the threshold for potential performance impairment (5 or more). This highlights the widespread presence of fatigue among researchers.

Mental Demand and Effort Drive Fatigue: Among the six dimensions of NASA-TLX, "mental demand" emerged as the strongest predictor of high fatigue. This suggests complex research activities that are particularly demanding of mental resources and effort.

Afternoon or Evening Shift Worsens Fatigue: Researchers working the afternoon or evening shift were significantly more likely to report high fatigue (86.8%) than those working the morning shift. This indicates that working hours and their alignment with circadian rhythms can significantly impact fatigue levels.

Sleep Deprivation Common: On average, researchers slept less than the recommended minimum of 7 hours per night. Over half (54.4%) slept less than 7 hours, and almost a third (27.8%) slept 6 hours or less, suggesting a concerning prevalence of sleep deprivation.

Frustration as a Potential Risk Factor in the Afternoon/Evening: Differences in frustration levels were observed across shifts, suggesting frustration might be another predictor of fatigue, particularly in the afternoon/evening shift. Further research is needed to explore this link.

3.5 Validation

This study revealed that "fatigue before starting a research shift," "conducting research in the afternoon or evening," and "average NASA-TLX score." are the factors that contribute to the researchers' cognitive fatigue. These results are analogous to the study conducted by Torres et al. titled "Evaluation of fatigue and workload among workers conducting complex manual assembly in manufacturing." They also found that baseline fatigue and working shifts are contributing factors to metal fatigue in the case of manual assembly workers. That study also utilized the logistics regression in the same way as this study. As the method used in this study has been popular in the scientific studies of cognitive ergonomics and similar studies have got analogous results, it is evident that the method and model are robust and matured enough.

4 Conclusion

The most contributing predictors of mental workload among researchers are "fatigue before starting a research shift," "conducting research in the afternoon or evening," and "average NASA-TLX score." Among all the dimensions of the NASA-TLX, "mental demand" and "effort" are the most critical ones for managing mental workload and cognitive fatigue in research or scholarly work. Thus, to avoid or reduce mental workload and fatigue, it is imperative to avoid working in the afternoon or evening and not conduct research when feeling fatigued and stressed.

This finding holds significant implications for both researchers and research institutions. For researchers, recognizing frustration as a potential trigger for fatigue can empower them to actively manage their workload, prioritize tasks, and seek support when needed. This, in turn, can contribute to their well-being and potentially enhance research productivity. First off, pre-assessment of the fatigue level and mental workload could be an invaluable technique to adopt the strategy to avoid the research work when already feeling fatigued, as one of the contributing factors of cognitive fatigue is "fatigue before starting a research shift." Another proposed strategy is schedule selection. If the research schedule is in the first half of the day, the mental fatigue could easily be bypassed. After all, 'Mental demand' and 'effort' intensive tasks should be given extra caution as these could easily make the researcher fatigued.

Although researchers from various institutions and research organizations were surveyed in this study, almost 85% of the participants were male, and almost 15% were female. The availability of female researchers and their willingness to provide data impacted the comparatively lower participation of female researchers. As this study takes a male-dominant survey, future research could address this issue by taking an equal portion of them. Besides, more sophisticated analysis could be carried out using EEG signal processing while engaged in research. This broader perspective ultimately paves the way for more effective interventions and strategies to combat fatigue, leading to a healthier, more productive future for researchers.

Moreover, our study focused on a single snapshot of fatigue rather than considering its cumulative effect over time. Understanding the accumulation of fatigue over consecutive days, including the influence of factors like sleep debt and recent shift changes, necessitates further inquiry. Future research could delve into this cumulative effect and its repercussions on fatigue levels. Notably, although sleep duration was assessed, sleep quality was not directly evaluated. By addressing these and broadening the scope of future research endeavors, we can attain a deeper comprehension of fatigue among researchers and devise effective strategies to manage and alleviate its impact on their well-being and performance.

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