

Assessing the Impact of Concurrent Employment and Undergraduate Studies on the Mental Workload of Student Virtual Assistants in the Philippines

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Abstract

Student virtual assistants (VAs) face unique challenges in managing academic responsibilities and work duties. This study investigated the mental workload (MWL) of student VAs ($n=23$) across two periods: the early semester (lighter academic demands) and the mid-semester (peak academic demands). Physiological MWL was assessed using the Muse 2 EEG device, measuring relative brainwave activity (alpha, beta, theta, gamma, delta). In contrast, subjective MWL was calculated using the NASA-Task Load Index (NASA-TLX). Results showed significantly higher relative beta ($p = 0.004$, $d = 0.674$) and gamma ($p = 0.009$, $d = 0.609$), and lower delta ($p = 0.002$, $d = 0.753$) during the heavy academic period, indicating increased stress, anxiety, and sleep deprivation. NASA-TLX scores were higher in the heavy academic period ($p < 0.001$, $d = 1.785$), with "Effort" and "Frustration" notably elevated. Findings highlighted that heavier academic demands increase cognitive and emotional strain, underscoring the need for strategies that promote a sustainable work-study setup.

Keywords

mental workload (MWL), virtual assistant (VA), electroencephalogram (EEG), NASA task load index (TLX), and working students

1. Introduction

The emergence of virtual workers has become a vital component of the modern workforce, significantly shaping the global job market (Dapiton and Gano-An 2023). A study by Pangarkar (2023) forecasted that the virtual task outsourcing market will reach \$544.8 billion in 2032. With the rise of digital jobs, many have turned to remote roles such as being a virtual assistant (VA), which offers flexibility and decent income potential comparable to traditional face-to-face jobs. As defined by Seranmadevi et al. (2022), VAs are independent part-time or full-time contractors who perform administrative tasks remotely, including management, scheduling, and online research work for their clients. The sudden transition to work-from-home setups has significantly increased remote work opportunities, especially in developing countries like the Philippines (Dapiton and Gano-An 2023).

According to a World Economic Forum (WEF) report, the Philippines ranked seventh among the world's fastest-growing remote work hubs, having a remarkable 60% growth in remote work opportunities (Gita-Carlos 2023). Given the continued rise of investors in the business process outsourcing (BPO) sector, remote jobs such as VAs have become rampant in the country (Calpo-Lugtu 2023). Since the Philippines offers an English-speaking workforce and a considerably cheaper labor market, the country has become one of the major centers for BPOs (Friginal 2007). Having

multiple economic challenges, the increased online work opportunities have influenced many Filipinos to enter the remote work industry (Vicaria 2023), particularly students who also work while completing their studies.

The Philippines' economic environment has long compelled many undergraduate students to join the workforce. As Aton et al. (2024) reported that based on the latest data from the Commission on Higher Education (CHED), about 216,000 students—around 8% of the country's total college population—were engaged in full-time or part-time work while completing their undergraduate studies. However, balancing these dual academic and professional responsibilities introduces a significant cognitive and emotional burden. A study by Bautista et al. (2023) found that 78.2% of remote working students in a university in the Philippines struggle with dual responsibilities which often translate into elevated levels of fatigue and burnout. As the semester advances, fatigue worsens (Grepo 2023), with workload intensifying from introductory tasks to heavier assessments towards the latter portion of the semester (Karma et al. 2021). These facts underscore that education in the Philippines demands academic excellence and resilience to thrive amidst heavy workloads and financial challenges.

Mental workload (MWL) is a complex, multifaceted construct influenced by task demands, individual capacities, expectations, and environmental contexts (Longo et al. 2022). High MWL can lead to burnout, poor academic performance, and job dissatisfaction (Gumasing et al. 2023; Maghsoud et al. 2022). In the study by Candelario et al. (2024), focusing on Filipino BPO workers, it was found that these workers are exposed to physical and psychological stress, sleep disturbances, and other occupational health risks, given the unique nature of their work. These risks are detrimental, particularly in the context of working students such as student VAs, who bear the weight of both academic and job-related stressors. While the flexibility of VA jobs are perceived as ideal for students, the cognitive demands of juggling work and study responsibilities remain substantial. As highlighted by Aquino and Seva (2017), quantifying MWL through both objective and subjective methods is vital to understanding the toll it takes on individuals. High MWL has been linked to impaired concentration, increased dropout rates, and growing doubts among students pursuing higher education (Kember and Leung 2006; Karma et al. 2021).

The increasing complexity of academic and professional duties being experienced by student VAs necessitates effective time management and support systems. However, empirical research on the mental workload of Filipino student VAs, especially during distinct academic periods, is limited. By analyzing the dual relationship of concurrent employment and undergraduate studies, this study evaluates the impact of the academic influence on the mental workload of student-virtual assistants in the Philippines.

1.1 Objectives

To address the abovementioned gaps, the study aims to assess the impact of concurrent employment and undergraduate studies on the mental workload of student VAs in the Philippines. Particularly, it seeks to use physiological and subjective measures to quantify mental workload, perform comparative analysis between light and heavy academic periods, and provide recommendations for effective workload management.

2. Literature Review

According to Russell (2020), the VA industry can be categorized into two main types, namely: the general VA and the specialized VA. In addition, Kenton (2024) imparted that general VAs are those that perform normal clerical duties, while specialized VAs have better expertise in specific areas, such as coding and performing updates on software and websites. With the rise of digital technology, many students have found remote work opportunities while studying for their college degrees due to its flexible working hours. The pandemic also influenced this student-work setup as it increased the number of student workers, with many going on to take on remote-based jobs to support their families while studying (Vicaria 2023). Working while studying is common in the Philippines due to economic constraints. Aton et al. (2024) reported that, based on Commission on Higher Education (CHED) data, about 216,000 students were working while completing their undergraduate studies. However, balancing these two responsibilities may increase the mental workload of student virtual assistants, potentially resulting in long-term negative effects. As noted by Gumasing et al. (2023), academic workload is a significant contributor to student burnout.

Mental workload (MWL) can be measured using a variety of physiological sensor data. Based on the study of Charles and Nixon (2019), physiological measures that objectively measure mental workload include the use of electroencephalographic, electrocardiographic, respiratory, dermal, blood pressure, and ocular measurements. According to Zhang and Cui (2022), an electroencephalogram (EEG) is an electrophysiological method of monitoring

and recording the brain's electrical activity. Nowadays, modern EEG devices use non-invasive scalp electrodes to detect voltage changes generated by neuronal activity. Such devices objectively record brain activity, enabling the identification of EEG signals associated with mental workload. (Antonenko et al. 2010; Makransky et al. 2019).

LaRocco et al. (2020) explained that EEG-based mental workload assessment relies on analyzing brain activity across frequency bands, namely alpha, beta, delta, gamma, and theta. Alpha waves are associated with relaxed and restful states (Wei et al. 2018), beta waves with alertness and focused cognitive processing (Abhang et al. 2016), delta waves with deep sleep (Wei et al. 2018), gamma waves with high-level cognitive functions such as memory and perception (Antonenko et al. 2010), and theta waves with creativity and deep relaxation (Abhang et al. 2016). Aquino and Seva (2017) applied EEG to assess the mental workload of 15 jeepney drivers during actual driving conditions and found evidence of poor sleep quality and elevated stress levels, as indicated by increased delta activity and reduced theta, alpha, and beta power. Similarly, Chaudhary et al. (2020) used the Muse 2 EEG device to evaluate mental workload during cognitive-motor integration tasks and demonstrated that variations in EEG frequency bands corresponded to changes in task demands. Despite the effectiveness of EEG in objectively capturing mental workload, substantial inter-individual variability in EEG power complicates group-level interpretation (Zhou et al. 2021); thus, relative brain power has been recommended as a normalization approach to improve comparability across participants (Klimesch 1999; Clarke et al. 2001; Bian et al. 2014).

Recognizing the multifaceted nature of mental workload is essential for workplace improvement; accordingly, the NASA Task Load Index (NASA-TLX) offers a widely used multidimensional subjective assessment tool (Hart & Staveland 1988). Despite the availability of other instruments, NASA-TLX remains the most applied method for subjective MWL measurement (Dias et al. 2018) and is preferred for its higher sensitivity, particularly under low mental workload conditions, compared with SWAT and CarMen-Q (Zahra et al. 2024).

The NASA-TLX measures mental workload across six dimensions—mental demand, physical demand, temporal demand, performance, effort, and frustration—using rating scales and pairwise comparisons (Hart & Staveland 1988). Mental, physical, and temporal demands reflect cognitive load, physical exertion, and time pressure, while performance and effort capture perceived task success and exertion (Zahra et al. 2024). Using this tool, Aquino and Seva (2017) found that jeepney drivers experienced very high mental workload, with mental demand as the primary contributor; Mayano (2022) reported that increased workload among public school teachers significantly reduced perceived autonomy; and studies on call center agents showed consistently high to very high workload levels across work-from-home, office-based, and hybrid arrangements.

From the analysis of related literature, three major research gaps were identified. First, as a developing field, MWL studies in the Philippines have only been dedicated to several professionals, such as jeepney drivers, public school teachers, and call-center agents, but part-time workers like student-VAs have not been explored yet (Aquino and Seva 2017; Mayano 2022; Ballad 2023). Second, most MWL studies, even from abroad, utilize only one method of measuring MWL, either purely subjective or purely objective, leaving a gap in understanding the connection between them, especially for those with dual roles (Dias et al 2018; Chaudhary et al 2020; Zhang and Cui, 2022). Third, there is limited research that focuses on measuring mental workload in a longitudinal research setup emphasizing the effect of increasing MWL, as MWL studies would often have a cross-sectional research design or occur in one period only (Bala 2020; Gumasing et al., 2023; Charles and Nixon 2019). These gaps limit the development of effective interventions. Literature indicates that student virtual assistants inevitably face high mental workload due to concurrent academic and remote work demands, making the use of both objective and subjective measures essential to prevent burnout and promote a sustainable work-study balance.

This study aims to examine the impact of academic workload on the mental workload of student virtual assistants in the Philippines. It employs a longitudinal design comparing light and heavy academic periods using both objective EEG-based measures and subjective assessment through the NASA-TLX. By integrating physiological and self-reported data, the study seeks to provide a more comprehensive understanding of how fluctuating academic demands influence the mental workload of working students over time.

3. Methods

The study used a longitudinal design to quantify mental workload through both objective and subjective measures, following Aquino and Seva (2017), to provide a comprehensive understanding of overall workload. Longitudinal

studies track the same individuals over time, allowing for the assessment of changes due to specific variables (Freeman et al. 2018). Data were collected across two experimental periods with an added academic influence variable.

A total of 23 male student VAs participated via purposive sampling, consistent with prior MWL studies requiring at least 12 participants (Aquino and Seva 2017; Chaudhary et al. 2020; Pavlov et al. 2021). Eligible participants were Filipino undergraduate students with a regular course load, working at least 10 hours per week as general virtual assistants, willing to provide consent, and free from substance abuse, neurological illness, brain injury, psychoactive drug use, or concussion.

Objective mental workload was measured using the Muse 2 EEG device (Byrne 2011; Zhang and Cui 2022), a portable, user-friendly headset transmitting data via Bluetooth. The device recorded alpha, beta, delta, gamma, and theta brainwave activity non-invasively through four electrodes placed according to the 10–20 system at a 12-bit, 256 Hz sampling frequency (Massa et al. 2023; Chaudhary et al. 2020). An illustration of the Muse 2 and electrode placement is shown in Figure 1.

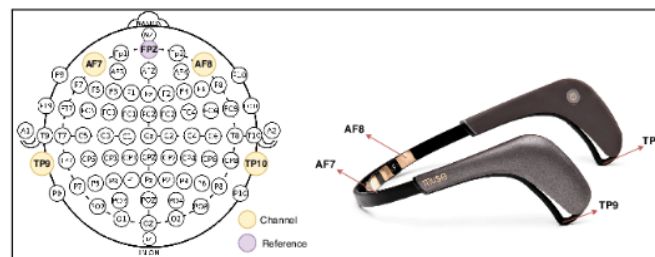


Figure 1. Placement of Muse 2 using the 10-20 system on the head.

A subjective mental workload assessment requires the participants to perform a task they usually do (Byrne 2011). Once completed, the participants are then instructed to answer the National Aeronautics and Space Administration's (NASA) Task Load Index (TLX) questionnaire, a widely recognized and research-validated tool for assessing mental workload (Mohammadi et al. 2013). The application employs six rating scales and 15 pairwise comparisons used to evaluate six mental workload components: (1) mental demand, (2) physical demand, (3) temporal demand, (4) performance, (5) effort, and (6) frustration. Figure 2 illustrates the NASA-TLX application used in the study.

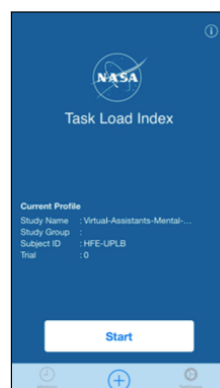


Figure 2. Mobile view interface of the official NASA-TLX application.

EEG data were collected using the Muse 2 headband and the Mind Monitor application, which records real-time signals and exports them as CSV files. The raw data were stored in Dropbox and retrieved for cleaning in MS Excel, including the removal of errors such as poor electrode contact and missing values. After verification, absolute and relative brain wave values were computed using Fast Fourier Transformation within the Mind Monitor application. Figure 3 illustrates the EEG data processing workflow.

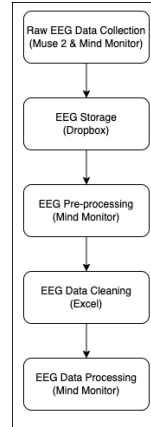


Figure 3. Data collection and processing of recorded EEGs.

The absolute values represent the raw intensities of alpha, beta, delta, gamma, and theta waves. The normal frequency ranges and associated conditions for each brain wave type, provided by Interaxon Inc., are shown in Table 1.

Table 1. Frequencies and associated mental states of brain waves.

Brain Wave	Frequency Range (Hz)	Associated Mental States
Alpha	8 – 13	Physically and mentally relaxed
Beta	13 – 32	Awake, alert consciousness, thinking, excitement
Delta	0.5 – 4	Deep dreamless sleep, loss of bodily awareness, repair
Gamma	32 – 100	Heightened perception, problem-solving, and cognitive processing
Theta	4 – 8	Creativity, insight, deep states, and deep meditation

Source: Interaxon Inc., 2024

Although EEG effectively measures mental workload, absolute brain wave power varies across individuals, limiting group-level comparisons (Zhou et al., 2021). Absolute power is also more vulnerable to session-to-session fluctuations; for instance, absolute delta power can vary by up to 28% within the same individual, whereas relative alpha power varies by only 7% (Liu et al., 2024). While both absolute and relative EEG power demonstrate high test–retest reliability (Salinsky et al., 1991), relative power shows smaller fluctuations across repeated recordings, indicating greater stability. This stability is crucial in EEG human factors research, where consistent baseline comparisons are required across sessions. Thus, relative brain power was used to reduce inter-subject variability and enable reliable comparisons across participants and periods, following established EEG practices (Klimesch, 1999; Clarke et al., 2001). Normative relative brain power values from prior studies are presented in Table 2.

Table 2. Normative relative brain power results from several studies

Studies	Relative Alpha	Relative Beta	Relative Delta	Relative Gamma	Relative Theta
Taylor et al. (2021)	0.192 - 0.204	0.182 - 0.200	0.250 - 0.270	0.110 - 0.130	0.222 - 0.234
Rempe et al. (2023)	0.200 - 0.350	0.065 - 0.085	0.350 - 0.500	0.020 - 0.035	0.210 - 0.240
Kozma et al. (2024)	0.210 - 0.240	0.200 - 0.230	0.280 - 0.310	N/A	0.250 - 0.270
Janiukstyte et al. (2023)	0.240 - 0.600	0.090 - 0.170	0.160 - 0.390	0.020 - 0.080	0.120 - 0.180

Janiukstyte et al. (2023) provided comprehensive relative EEG data using MEG, scalp EEG, and intracranial EEG. In this study, the Mind Monitor application used Fast Fourier Transform (FFT) to compute brain wave frequencies and intensities, and relative values for Period 1 and Period 2 were compared using a Paired Sample T-Test. The Muse 2 device was calibrated through pilot trials, and normalization minimized individual amplitude variability, supporting detection of workload-related changes (Klimesch, 1999).

The NASA-TLX measures six workload dimensions—mental, physical, and temporal demand, performance, effort, and frustration (Hart and Staveland, 1988; Zahra et al., 2024). Final weighted scores, generated through validated pairwise comparisons (Mohammadi et al., 2013; Dias et al., 2018; Zahra et al., 2024), were compared between Period 1 and Period 2 using a Paired T-Test.

4. Data Collection

Participants performed clerical virtual assistant tasks under standardized guidelines. At least one day before the experiment, they were instructed to avoid alcohol and hairstyling products, ensure a quiet environment, and review the study information and consent forms. The study involved non-invasive physiological measurements and questionnaires with adult male volunteers, all of whom provided written informed consent under minimal-risk ethical standards.

After confirming compliance, Period 1 data collection began. The Muse 2 device was placed on the forehead and behind the ears and connected to the Mind Monitor application to check signal quality. A three-minute trial run was conducted, using the app's horseshoe indicator to verify connection strength (solid ovals = good, outlined = poor, none = no connection), as shown in Figure 4.

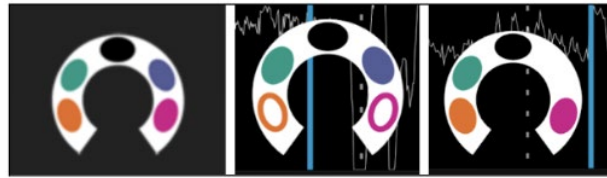


Figure 4. Horseshoe indicators in the Mind Monitor application.

Data recording (minimum of 65 minutes) began only after stable signal indicators were confirmed. Participants were instructed to avoid eating, drinking, or standing to prevent EEG artifacts and were continuously monitored to ensure safety and proper Muse 2 placement. An example of the experimental setup is shown in Figure 5.

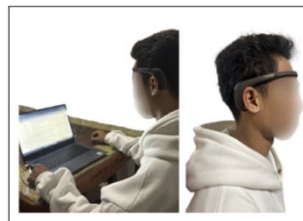


Figure 5. An example of the experiment setup with proper placement of Muse 2.

After EEG data collection, participants completed the NASA-TLX assessment via the official mobile application, which includes 15 pairwise comparisons across six workload components. The application automatically generated component scores, concluding data collection for Period 1, after which the data were processed. At least 49 days later, Period 2 data were collected using the same procedure. The datasets from both periods were then processed and compared to assess changes in participants' mental workload.

5. Results and Discussion

5.1 Numerical Results

Participants came from seven universities and colleges in Region IV-A (CALABARZON), representing 17 academic programs and diverse perspectives. They were aged 18–23, with most aged 21–22, and 68% were in their 3rd or 4th year, indicating substantial academic and virtual assistant responsibilities. The following section presents objective mental workload results based on relative brain wave power during light (P1) and heavy (P2) academic periods. Using the Muse 2 EEG device and Mind Monitor application, relative Alpha, Beta, Gamma, Theta, and Delta power were computed per participant; a partial dataset is shown in Table 3, with the full data available upon request.

Table 3. Summary of computed relative brain waves.

ID	REL. ALPHA		REL. BETA		REL. DELTA		REL. GAMMA		REL. THETA	
	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P001	0.25	0.254	0.141	0.164	0.363	0.286	0.04	0.095	0.206	0.201
P002	0.292	0.266	0.149	0.151	0.323	0.326	0.04	0.049	0.195	0.208
...	...	...	...	...	...	...	...	...	...	...
P023	0.274	0.273	0.132	0.128	0.342	0.365	0.033	0.031	0.219	0.203

Relative brain wave values were normalized as proportions of total brain activity, enabling comparisons across participants and periods by accounting for individual differences in EEG signal strength. Normality of paired differences between periods was assessed using the Shapiro–Wilk test at $\alpha = 0.05$ as shown in Table 4. After confirming normality, relative brain wave values for the two periods were compared using a Paired Sample T-Test, with results shown in Table 5.

Table 4. Summary of the test for normality for relative brain waves.

Comparison of relative brain waves	Paired Differences at $\alpha = 0.05$				
	Mean	Std. Deviation	Std. Error Mean	P-value*	Test to be used
P2 alpha – P1 alpha	0.017	0.058	0.012	0.867	Paired T-Test
P2 beta – P1 beta	0.033	0.048	0.01	0.968	Paired T-Test
P2 delta – P1 delta	-0.063	0.084	0.018	0.823	Paired T-Test
P2 gamma – P1 gamma	0.017	0.027	0.006	0.223	Paired T-Test
P2 theta – P1 theta	-0.007	0.021	0.004	0.401	Paired T-Test

Table 5. Summary of Paired T-Test for relative brain waves.

Comparison of relative brain waves	Paired Differences at $\alpha = 0.05$					
	Test statistic	P-value	Significance	Cohen's d	95% CI	Observed Effect
P2 alpha – P1 alpha	1.395	0.177	Not significant	0.291	[-0.14, 0.73]	Small
P2 beta – P1 beta	3.231	0.004	Significant	0.674	[0.26, 1.12]	Medium
P2 delta – P1 delta	-3.614	0.002	Significant	-0.753	[-1.18, -0.32]	Medium
P2 gamma – P1 gamma	2.855	0.009	Significant	0.609	[0.20, 1.06]	Medium
P2 theta – P1 theta	-1.702	0.103	Not significant	-0.355	[-0.77, 0.10]	Small

In summary, the Shapiro–Wilk test demonstrated that the paired differences for all the brain waves, Alpha, Beta, Delta, Gamma, and Theta waves, were normally distributed; hence, allowing for the use of PSTT in all cases. These findings

provide the statistical foundation for the subsequent analyses of the significance of changes in brain wave activity across the two periods.

The statistical analysis of brainwave activity across P1 (light academic workload period) and P2 (heavy academic workload period) revealed significant changes in beta (p-value = 0.004), delta (p-value = 0.002), and gamma waves (p-value = 0.009), while the alpha (p-value = 0.177) and theta waves (p-value = 0.103) showed no significant differences. Based on the reviewed literature, the following interpretations are drawn.

Delta waves, associated with restorative sleep, significantly decreased from P1 to P2, a pattern commonly linked to sleep deprivation (Cohen et al. 2017; Fell et al. 2019). This suggests reduced sleep duration or quality during the heavy academic workload. In contrast, beta and gamma waves, associated with cognitive activity and task engagement, showed significant increases. Although these increases may reflect heightened cognitive processing (Cajochen et al. 1995), they are also associated with sleep deprivation (Corsi-Cabrera et al. 1992; Forest and Godbout 2000), indicating possible compensatory neural responses rather than improved cognition. Alpha and theta waves remained stable across periods, suggesting no substantial change in baseline relaxation or attention. Overall, the decreased delta and increased beta and gamma activity indicate elevated mental workload and potential sleep deprivation from P1 to P2, as heightened neural excitation may suppress the brain's shift to low-frequency rhythms necessary for high-quality sleep.

After comparing the results of the relative brainwaves and their corresponding normative ranges in the study of Janiukstyte et al. (2023). The following insights were drawn. While Beta wave activity in P1 remained within the normative range, P2 Beta activity increased and eventually exceeded the threshold. The heightened Beta activity aligns with literature that associates excessive Beta waves with increased anxiety, hyperarousal, stress, and symptoms such as sleep disturbances, obsessiveness, and hyperactivity (Scottsdale Neurofeedback Institute 2024). The rise in Beta waves during Period 2 may indicate elevated mental strain as academic demands intensified. Theta wave activity exceeded normative ranges in both Period 1 and Period 2. The elevated Theta activity during awake states can indicate difficulties in focus and attention, potentially linked to hyperactivity and impulsivity (Center for Attention Deficit & Learning Disorder 2024). The persistence of excessive Theta waves across both periods suggests ongoing challenges in terms of focus and attention due to the dual roles that a student-VA performs.

The subjective mental workload data were gathered using the NASA-TLX. The adjusted scores for each component were derived from the product of two factors: the raw ratings provided by each participant for the specific component and their corresponding weights assigned to that component based on the results of the pairwise comparisons among the six workload components. The summary of the adjusted scores per participant is shown in Table 6 below. The complete dataset is available upon request.

Table 6. Summary of adjusted scores for each component of the NASA-TLX.

ID	MD		PD		TD		PE		EF		FR	
	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
P001	260	400	0	0	350	240	70	80	110	140	60	210
P002	280	350	15	0	375	210	120	50	120	210	0	130
...	...	...	...	...	...	...	...	...	...	...	...	...
P023	350	350	0	20	150	120	75	35	30	60	135	260

Legend: MD – mental demand, PD – physical demand, TD – temporal demand, PE – performance, EF – effort, and FR – frustration

The NASA-TLX adjusted scores for each component, and the main weighted rating (MWR) were tested for normality using the Shapiro-Wilk. The MWR is the aggregated score of the weighted mental workload components. The results of the normality test, $\alpha = 0.05$, and the ideal paired difference test to be used per component are shown in Table 7.

Table 7. Summary of the test for normality for NASA-TLX components.

Comparison of NASA-TLX components	Paired Differences at $\alpha = 0.05$				
	Mean	Std. Deviation	Std. Error Mean	P-value	Test to be used
P2 MD – P1 MD	9.13	97.86	20.405	0.771	Paired T-Test
P2 PD – P1 PD	1.304	10.359	2.16	<0.001*	Paired T-Test
P2 TD – P1 TD	-12.826	97.478	20.325	0.807	Paired T-Test
P2 PE – P1 PE	-1.304	42.539	8.87	0.346	Paired T-Test
P2 EF – P1 EF	73.696	78.033	16.271	0.279	Paired T-Test
P2 FR – P1 FR	75	61.144	12.749	0.758	Paired T-Test
P2 MWR – P1 MWR	9.666	5.416	1.129	0.772	Paired T-Test

Each component of the NASA-TLX was tested for significant differences using a paired sample t-test, although the Shapiro-Wilk test indicated non-normality ($p < 0.001$) for PD, a paired t-test was used because it is robust to moderate deviations from normality. Results were confirmed with a Wilcoxon signed-rank test. Statistical significance was determined at $\alpha = 0.05$, with effect sizes calculated to quantify the magnitude of the observed effects. The results of the tests are shown in Table 8.

Table 8. Results from SPSS for NASA-TLX components.

Comparison of NASA-TLX components	Paired Differences at $\alpha = 0.05$					
	Test Statistic	P-value	Significance	Cohen's D	95% CI	Observed Effect
P2 MD – P1 MD	0.447	0.659	not significant	0.093	[-0.32, 0.50]	Very Small
P2 PD – P1 PD	0.604	0.552	not significant	0.155	[-0.28, 0.54]	Low
P2 TD – P1 TD	-0.631	0.535	not significant	-0.132	[-0.54, 0.28]	Very Small
P2 PE – P1 PE	-0.147	0.884	not significant	0.031	[-0.44, 0.38]	Very Small
P2 EF – P1 EF	4.529	<0.001	significant	0.944	[0.45, 1.44]	Large
P2 FR – P1 FR	5.883	<0.001	significant	1.227	[0.69, 1.77]	Large
P2 MWR – P1 MWR	8.642	<0.001	significant	1.785	[1.13, 2.44]	Large

The results from SPSS for the NASA-TLX components and the Main Weighted Rating provide an in-depth analysis of how participants perceived changes in workload across the light academic work period (P1) and the heavy academic work period (P2). Specifically, there was a significant increase in the Effort component, indicating that participants need to allocate more mental or physical resources to complete their tasks. The increased frustration is associated with higher levels of emotional stress experienced by participants during the heavy academic workload period. It is aligned with the observed significant increase in beta that went beyond the normative range, which is often associated with anxiety and stress.

Meanwhile, other NASA-TLX components showed no significant differences between the two periods. For Mental Demand, participants perceived that the mental requirements of the VA task remained consistent across both periods. For Physical Demand, the tasks did not require increased physical activity across two periods for the virtual clerical roles performed by VAs. For Temporal Demand, participants did not report increased time pressure, possibly due to the flexible time schedules under which a VA performs his or her tasks. For performance, the perceived success and output remained stable, indicating that participants felt they achieved similar task success in two periods.

The findings suggest that while participants exerted more resources (Effort) to maintain task performance and engagement, they experienced increased stress and annoyance (Frustration). The rise in effort and frustration, together with the main weighted rating of MWL using NASA-TLX, highlights the worsening of the MWL faced by virtual assistants balancing dual responsibilities during P2.

5.2 Proposed Improvements

In summary, the findings suggest that while VAs can work under increased academic workload conditions, this comes at the cost of higher effort and frustration, alongside potential challenges caused by sleep deprivation, stress, and

anxiety. The observed changes in EEG activity and NASA-TLX components highlight the burden of academic and professional responsibilities on VAs' mental well-being. Hence, it is said that the student VAs should limit academic course workload or units, if possible, to at least the minimum requirements, before the start of the semester, to help mitigate MWL problems during high academic workload periods. Academic institutions can also employ policies such as having asynchronous lectures, flexible deadlines, and hybrid deliveries of courses. As for employers, a flexible working schedule can be implemented to balance their available time for both university and VA related works. In addition, given the observed decrease in Delta waves and increase in Beta and Gamma, indicating potential sleep deprivation, VAs should prioritize adequate sleep to maintain cognitive performance and emotional well-being. Hence, student VAs should adopt structured schedules and tasks to manage academic workload effectively. Finally, student VAs should join relevant mental workload management programs and services if their employers and educational institutions offer them.

Although the study has led to some significant findings, several points for improvement can still be addressed. While the current setup combines objective and subjective assessments to understand the mental workload, relying on Muse 2 with dry electrodes may restrict signal quality compared to gel-based EEG systems. Other software, like EEGLAB or Brainstorm, can provide a more robust artifact removal and signal interpretation. Furthermore, the study focused solely on EEG and subjective self-reports, excluding other physiological indicators such as heart rate variability (HRV) and galvanic skin response (GSR), which could also provide additional information to better understand the mental workload among the participants. Future studies must also seek formal institutional ethics approval and expand the scope of the ethical oversight. Only male participants with general VA classification were included because thick hair along the sides of the head can interfere with the fit and signal quality of the Muse 2; however, future research should also consider the inclusion of female participants and specialized VA classification for enhanced generalizability of the study. Finally, the study did not determine the optimal combined mental workload for student-VAs per semester, which future research may address to better understand performance in dual roles.

6. Conclusion

Integrating EEG and NASA-TLX results provides a comprehensive and complementary picture of how mental workload changes across P1 and P2. The EEG findings revealed the worsening of MWL, as supported by reduced sleep quality or sleep deprivation, associated with increases in Beta (p-value = 0.004) and Gamma (p-value = 0.009), and a decrease in Delta (p-value = 0.002) wave powers. It is also important to note how the significant increase in beta was beyond the normative range provided by the literature, indicating that the student VAs experienced anxious thinking, sleep difficulties, and worsened MWL in P2. These changes align with the significant increases in perceived Effort, Frustration, and Main Weighted Rating in the NASA-TLX results, suggesting that participants experienced greater mental and emotional strain during the heavy workload period. Hence, student VAs should consider limiting their academic units before the semester begins and adopt structured schedules to better manage peak academic workload periods, while prioritizing adequate sleep to maintain cognitive and emotional well-being. Meanwhile, academic institutions and employers can support them through flexible policies such as asynchronous lectures, hybrid delivery, adjustable deadlines, and flexible work schedules, as well as offering mental workload management programs.

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