

Subjective, Behavioral, and Physiological Responses to Cognitive Workload in Individuals with Chronic Non-Specific Low Back Pain and Healthy Controls

Zahra Rastgordani

University of Social Welfare and Rehabilitation Sciences

Hamid Reza Mokhtarinia

harmokhtarinia@yahoo.com

University of Social Welfare and Rehabilitation Sciences

Mohsen Vahedi

University of Social Welfare and Rehabilitation Sciences

Markus Melloh

University of Applied Sciences and Arts Northwestern Switzerland

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Abstract

Background

Cognitive workload can influence performance and physiological responses during computer-based work, but these responses remain insufficiently understood in individuals with chronic non-specific low back pain (CNSLBP). This study investigated subjective, behavioral, electromyographic, and cardiac responses to increasing cognitive workload in individuals with CNSLBP and healthy controls during a dual-task computer-based paradigm.

Methods

Thirty participants, including 15 individuals with CNSLBP and 15 healthy controls, completed four experimental conditions combining two typing-speed levels and two cognitive workload levels. Subjective workload was assessed using the NASA Task Load Index (NASA-TLX). Behavioral performance and typing errors were recorded, while physiological responses were assessed using facial electromyography (EMG) and heart rate. Outcomes were analyzed using mixed repeated-measures analysis of variance to examine the effects of experimental condition, group, and their interaction.

Results

Increasing task demands significantly increased perceived workload ($F = 34.63$, $p < 0.001$) and reduced behavioral performance ($F = 31.12$, $p < 0.001$), whereas typing errors did not change significantly. No significant between-group differences were observed in perceived workload or behavioral performance. In contrast, participants with CNSLBP exhibited significantly greater RMS activity in the corrugator supercilii and frontalis muscles (both $p < 0.001$), and a significant condition $\times$ group interaction was observed for corrugator RMS ($p = 0.018$). Heart rate did not differ significantly across experimental conditions or between groups.

Conclusions

Individuals with CNSLBP maintained subjective workload ratings and behavioral performance comparable to healthy controls but exhibited greater facial muscle activation during task performance. These findings suggest that maintaining performance under cognitive demands may require greater physiological effort in individuals with CNSLBP. Multimodal assessment combining subjective, behavioral, and physiological measures may provide a more comprehensive understanding of cognitive workload responses in people with chronic low back pain.

Background

Modern work environments increasingly require workers to process large volumes of information, manage multiple tasks simultaneously, and maintain performance under conditions of time pressure and frequent interruptions [1, 2]. Such demands place considerable strain on limited cognitive resources and contribute to increased mental workload, a construct reflecting the proportion of cognitive and attentional capacity required to meet task demands [3–6]. Mental workload has become a central concern in ergonomics because excessive workload is associated with impaired decision-making, reduced performance, increased fatigue, and a greater likelihood of human error [7, 8]. According to cognitive resource theories, cognitive resources are finite and must be distributed across competing tasks; consequently, performance may deteriorate when task demands exceed available resources [8–12]. Dual-task paradigms have therefore been widely used to investigate workload-related changes in human performance because they closely resemble occupational situations in which individuals must perform concurrent tasks [3, 13, 14]. Previous research has demonstrated that increasing task difficulty elevates perceived workload and alters physiological responses, even when overt behavioral performance remains relatively stable [15, 16].

Mental workload assessment has evolved from reliance on subjective ratings toward multidimensional approaches integrating behavioral, physiological, and subjective indicators [8, 17]. Subjective measures such as the NASA Task Load Index (NASA-TLX) remain widely used because of their practicality and sensitivity to workload manipulations [18, 19]. However, subjective ratings alone may not fully capture the underlying effort required to maintain task performance under demanding conditions [8, 17]. Consequently, physiological indicators such as heart rate variability (HRV), eye-tracking, electroencephalography (EEG), and electromyography (EMG) are increasingly used to characterize workload-related adaptations [20, 21]. Physiological responses provide valuable information regarding the mechanisms through which individuals regulate performance when cognitive demand increase [1, 22]. Therefore, integrating subjective, behavioral, and physiological measures may provide a more comprehensive understanding of workload-related adaptations than any single measure alone.

This issue may be particularly relevant in individuals with chronic non-specific low back pain (CNSLBP). Beyond its musculoskeletal manifestations, persistent pain may influence attention, information processing, and resource allocation by continuously competing for limited cognitive resources [23, 24]. Individuals with chronic pain frequently report difficulties in sustained attention, executive functioning, and task performance [24–27]. Furthermore, pain-related distress, fear-avoidance beliefs, and functional limitations may increase the cognitive demands associated with occupational activities [28, 29]. Consequently, when workload increases, individuals with CNSLBP may require greater physiological and cognitive effort to maintain task performance [23]. Although previous studies have suggested that pain can influence both behavioral and physiological responses to cognitive challenges, the mechanisms through which individuals with CNSLBP adapt to increasing mental workload remain incompletely understood [23, 30].

An important unresolved question is whether behavioral performance measures alone are sufficient to characterize workload-related adaptations in individuals with chronic low back pain [31, 32]. Although

previous studies have investigated mental workload, physiological responses, and low back pain separately [23, 33], limited evidence is available regarding whether individuals with chronic non-specific low back pain exhibit greater physiological activation while maintaining comparable behavioral performance under increasing cognitive demands [34, 35]. This distinction is important because workload-related adaptations may not be fully captured by performance measures alone [36–38]. Consequently, individuals experiencing chronic pain may appear to perform adequately while experiencing elevated physiological strain that remains undetected by conventional behavioral assessments. Therefore, the present study investigated the effects of increasing cognitive workload on subjective mental workload, behavioral performance, performance errors, facial electromyographic activity, and heart rate in healthy individuals and patients with chronic non-specific low back pain. We hypothesized that increasing cognitive demands would increase perceived workload and physiological activation in both groups and that individuals with chronic non-specific low back pain would show evidence of greater physiological effort despite broadly comparable behavioral performance outcomes.

Methods

Study Design

This controlled laboratory-based study was conducted in 2025 at the University of Social Welfare and Rehabilitation Sciences, Tehran, Iran. The study employed a mixed repeated-measures design to investigate the effects of increasing cognitive workload on subjective, behavioral, electromyographic, and cardiac responses in individuals with chronic non-specific low back pain (CNSLBP) and healthy controls. Participants completed four experimental conditions combining different levels of cognitive workload and typing task demands, allowing the examination of both within-subject (condition) and between-subject (group) effects.

Participants

Thirty participants, including 15 individuals with chronic non-specific low back pain (CNSLBP) and 15 healthy controls, were recruited from students and staff members of the University of Social Welfare and Rehabilitation Sciences.

Eligible participants were between 18 and 50 years of age, had at least one year of regular computer-use experience, and were able to complete the experimental protocol. Participants in the CNSLBP group reported non-specific low back pain persisting for at least 12 weeks [39]. Exclusion criteria included severe pain, significant psychological distress, neurological disorders, inadequate sleep prior to testing, recent intensive cognitive activity, alcohol consumption, or the use of medications affecting central nervous system function.

All participants provided written informed consent before participation. Sample size was estimated based on a previous study [40]. Assuming a significance level of 0.05 and statistical power of 80%, a

minimum of 12 participants per group was required [41]. To account for potential attrition, 15 participants were recruited for each group.

Apparatus

Surface electromyographic (EMG) activity was recorded using a DataLOG W4X8 system (Biometrics Ltd., Newport, UK). Bipolar surface electrodes were placed over the left corrugator supercilii and right frontalis muscles according to established facial EMG electrode-placement procedures [42]. A reference electrode was positioned over the ulnar styloid process. Prior to electrode placement, the skin was cleaned with alcohol to reduce electrode–skin impedance [43].

Heart rate was recorded using an Apple Watch SE (2nd generation; Apple Inc., Cupertino, CA, USA). Previous studies have reported acceptable accuracy of Apple Watch devices for heart rate monitoring under a range of experimental conditions [44].

Cognitive workload was manipulated using computer-based mental arithmetic tasks with two levels of difficulty, which were performed concurrently with typing tasks of different durations to create four experimental conditions [40]. Subjective mental workload was assessed using the NASA Task Load Index (NASA-TLX) [45].

Experimental Procedure

Following screening and informed consent, demographic information was collected and participants were prepared for physiological recordings. Surface EMG electrodes and the heart rate monitoring device were attached prior to testing, and signal quality was verified before data collection.

The primary task consisted of computerized data entry in Microsoft Excel. To account for individual differences in typing ability, participants first completed a 2-min calibration trial at their preferred typing speed. Individual typing speed was subsequently used to standardize task demands across experimental conditions. Participants completed typing tasks under two time-demand conditions: a standard-duration condition and a shortened-duration condition, in which the same amount of data entry was completed within 75% of the time allocated to the standard condition.

Cognitive workload was manipulated using auditory mental arithmetic tasks presented through headphones at 6-s intervals [40]. The low-workload condition involved summation of three single-digit numbers (e.g., $A + B + C$), whereas the high-workload condition involved multi-step arithmetic operations using five single-digit numbers (e.g., $A + B - C + D * E$) [46]. Participants were instructed to record their answers on a response sheet while simultaneously performing the typing task.

Four experimental conditions were created by combining two typing-task demand levels (standard and shortened duration) with two cognitive workload levels (low and high). The order of conditions was

randomized for each participant to minimize potential order effects. Each condition was followed by a 5-min rest period. Perceived mental workload was assessed using the NASA-TLX immediately after completion of each condition.

Typing performance, typing errors, facial EMG activity, and heart rate were recorded during each experimental condition.

Outcome Measures

Outcome Measures

Subjective Mental Workload

Perceived mental workload was assessed using the NASA Task Load Index (NASA-TLX). Participants completed the questionnaire immediately after each experimental condition [47]. The NASA-TLX provides a multidimensional assessment of perceived workload across six domains: mental demand, physical demand, temporal demand, performance, effort, and frustration. Higher scores indicate greater perceived workload [45].

Behavioral Performance

Behavioral performance during the typing task was quantified using a weighted performance index derived from correct responses, incorrect responses, and omitted responses. Correct responses were assigned a weight of + 1, incorrect responses a weight of - 0.25, and omitted responses a weight of - 1. The performance index was calculated as:

$$\text{Performance Index} = (\% \text{ Correct} \times 1) + (\% \text{ Incorrect} \times -0.25) + (\% \text{ Omitted} \times -1)$$

This approach was used to distinguish between inaccurate responding and complete response omission under increasing task demands [14, 48].

Performance Errors

Typing accuracy was evaluated using a performance error measure calculated as the proportion of incorrectly entered data relative to the total number of entered items. Higher values indicated poorer task accuracy [49, 50].

Electromyographic Activity

Facial muscle activity was assessed using surface electromyography (EMG) recorded from the corrugator supercilii and frontalis muscles. For each muscle, root mean square (RMS) and zero-crossing

rate (ZCR) were extracted as indicators of muscle activation amplitude and temporal characteristics of muscle activation, respectively [51, 52].

Heart Rate

Heart rate (HR) was recorded during each experimental condition using the optical heart rate sensor of an Apple Watch SE (2nd generation). HR was used to examine cardiovascular responses to variations in cognitive workload and task demands [44].

Signal Processing

EMG signals were recorded according to SENIAM recommendations, sampled at 1000 Hz, and exported to MATLAB (MathWorks Inc., Natick, MA, USA) for offline processing. Signals were band-pass filtered (20–450 Hz), full-wave rectified, and normalized using an intra-subject normalization procedure to reduce inter-individual variability. For each trial, the mean of the five highest initial signal peaks was used as a reference value, and signal amplitudes were normalized relative to this reference [53, 54]. Root mean square (RMS) and zero-crossing rate (ZCR) were subsequently calculated for the corrugator supercilii and frontalis muscles. RMS was used as an indicator of muscle activation amplitude, whereas ZCR was used to characterize the temporal properties of the EMG signal and motor unit activation patterns [52, 55].

Statistical Analysis

Statistical analyses were performed using SPSS version 22.0 (IBM Corp., Armonk, NY, USA). Descriptive statistics are presented as mean $\pm$ standard deviation. A mixed repeated-measures ANOVA was conducted with experimental condition (four task conditions combining typing duration and cognitive workload level) as the within-subject factor and group (healthy control vs. CNSLBP) as the between-subject factor. Main effects of condition and group, as well as condition $\times$ group interactions, were examined for all outcome measures.

Mauchly's test was used to assess sphericity, and Greenhouse–Geisser corrections were applied when necessary. Homogeneity of variance was evaluated using Levene's test. Bonferroni-adjusted pairwise comparisons were performed for significant effects. Partial eta squared (η^2p) was reported as the measure of effect size, and statistical significance was set at $p < 0.05$.

Results

Participant Characteristics

Demographic and clinical characteristics of the participants are presented in Table 1. No significant between-group differences were observed for age, stress, anxiety, or depression scores (all $p > 0.05$). The mean pain intensity in the CNSLBP group was 4.53 ± 0.99 , with an average pain duration of 24.20 ± 17.95 months. The mean Spinal Function Index (SFI) score in the CNSLBP group was 61.33 ± 16.38 .

Table 1
Demographic and clinical characteristics of the study participants

Variable	Healthy (n = 15)	CNSLBP (n = 15)	p-value
Age (years)	26.20 ± 6.76	25.47 ± 8.10	0.79
Male/Female, n	9 / 6	10 / 5	—
Stress (DASS-21)	16.07 ± 3.47	19.07 ± 6.30	0.117
Anxiety (DASS-21)	5.07 ± 5.75	9.20 ± 5.60	0.056
Depression (DASS-21)	8.93 ± 4.71	12.00 ± 6.84	0.164
Pain intensity (NPRS)	—	4.53 ± 0.99	—
Pain duration (months)	—	24.20 ± 17.95	—
Spinal Function Index (SFI)	—	61.33 ± 16.38	—

Table 1. here

Subjective Mental Workload and Behavioral Outcomes

Descriptive statistics for subjective mental workload, performance scores, and typing error rates across the four experimental conditions are presented in Table 2. Results of the repeated-measures ANOVA are summarized in Table 3.

Table 2
Means and standard deviations of subjective mental workload and behavioral outcomes across experimental conditions

Outcome	Group	C1	C2	C3	C4
NASA-TLX	Healthy	10.33 ± 2.24	12.82 ± 3.11	10.79 ± 2.84	12.35 ± 2.32
	CNSLBP	9.22 ± 3.28	12.93 ± 3.38	9.36 ± 3.27	12.48 ± 3.28
Performance score	Healthy	-25.08 ± 10.15	-53.84 ± 11.90	-44.23 ± 10.08	-55.57 ± 6.25
	CNSLBP	-26.52 ± 24.41	-48.44 ± 14.58	-39.89 ± 8.86	-49.24 ± 14.17
Typing error (%)	Healthy	1.02 ± 0.94	0.74 ± 0.98	0.75 ± 0.65	0.74 ± 0.99
	CNSLBP	0.47 ± 0.78	0.87 ± 0.87	0.52 ± 0.53	0.77 ± 1.02
C1 = 5-min typing + low cognitive load, C2 = 5-min typing + high cognitive load					
C3 = 3.5-min typing + low cognitive load, C4 = 3.5-min typing + high cognitive load					

Table 3
Repeated-measures ANOVA results for subjective mental workload and behavioral performance outcomes.

Outcome	Condition F(p)	η^2p	Group F(p)	η^2p	Condition $\times$ Group F(p)	η^2p
NASA-TLX	34.63 (< 0.001)	0.553	0.34 (0.56)	0.012	2.29 (0.085)	0.075
Performance score	31.12 (< 0.001)	0.520	1.33 (0.25)	0.045	0.63 (0.59)	0.022
Typing error (%)	0.25 (0.85)	0.009	0.60 (0.44)	0.021	1.14 (0.33)	0.039

A significant main effect of condition was observed for NASA-TLX scores ($F(3,84) = 34.63$, $p < 0.001$, $\eta^2p = 0.553$), indicating increased perceived workload under more demanding task conditions. However, neither the main effect of group ($F(1,28) = 0.34$, $p = 0.56$) nor the condition $\times$ group interaction ($F(3,84) = 2.29$, $p = 0.085$) reached statistical significance.

Similarly, performance scores differed significantly across experimental conditions ($F(3,84) = 31.12$, $p < 0.001$, $\eta^2p = 0.520$). Post-hoc comparisons indicated lower performance in conditions involving greater task demands. No significant main effect of group ($F(1,28) = 1.33$, $p = 0.25$) or condition $\times$ group interaction ($F(3,84) = 0.63$, $p = 0.59$) was found.

For typing error rate, neither the main effect of condition ($F(3,84) = 0.25$, $p = 0.85$), the main effect of group ($F(1,28) = 0.60$, $p = 0.44$), nor the interaction effect ($F(3,84) = 1.14$, $p = 0.33$) was significant. These findings suggest that increasing task demands increased perceived workload and reduced performance, while typing accuracy remained relatively stable across conditions and groups.

Table 2. Here

Table 3. Here

Electromyographic Outcomes

Descriptive statistics for electromyographic outcomes are presented in Table 4, and repeated-measures ANOVA results are summarized in Table 5.

Table 4

Means and standard deviations of electromyographic outcomes across experimental conditions

Outcome	Group	C1	C2	C3	C4
RMS Corrugator	Healthy	0.158 ± 0.052	0.108 ± 0.025	0.141 ± 0.053	0.119 ± 0.052
	CNSLBP	0.234 ± 0.046	0.217 ± 0.104	0.256 ± 0.070	0.147 ± 0.091
RMS Frontalis	Healthy	0.160 ± 0.059	0.147 ± 0.048	0.170 ± 0.050	0.134 ± 0.063
	CNSLBP	0.249 ± 0.063	0.234 ± 0.111	0.210 ± 0.079	0.196 ± 0.083
ZCR Frontalis	Healthy	48860 ± 9531	51393 ± 6031	48602 ± 7084	49729 ± 8271
	CNSLBP	47324 ± 4751	47858 ± 4814	50187 ± 1348	50118 ± 904
ZCR Corrugator	Healthy	47593 ± 8575	49317 ± 6961	47221 ± 6275	50786 ± 7258
	CNSLBP	45186 ± 11841	45385 ± 11723	44181 ± 4361	45254 ± 13403

Table 5

Repeated-measures ANOVA results for electromyographic outcomes

Variable	Condition Effect F (p)	η^2p	Group Effect F (p)	η^2p	Condition × Group Effect F (p)	η^2p
RMS Corrugator	8.52 (< 0.001)	0.233	27.96 (< 0.001)	0.500	3.56 (0.018)	0.113
RMS Frontalis	2.07 (0.111)	0.069	15.90 (< 0.001)	0.362	1.07 (0.367)	0.037
ZCR Frontalis	1.50 (0.210)	0.051	0.16 (0.680)	0.006	2.91 (0.030)	0.094
ZCR Corrugator	0.65 (0.580)	0.023	1.39 (0.240)	0.047	0.60 (0.610)	0.021

Root Mean Square (RMS)

For the corrugator supercilii muscle, significant main effects of condition ($F(3,84) = 8.52$, $p < 0.001$, $\eta^2p = 0.233$) and group ($F(1,28) = 27.96$, $p < 0.001$, $\eta^2p = 0.500$) were observed. A significant condition × group interaction was also found ($F(3,84) = 3.56$, $p = 0.018$, $\eta^2p = 0.113$). RMS values were consistently higher in the CNSLBP group across all conditions, and the magnitude of between-group differences varied across experimental conditions. For the frontalis muscle, no significant effect of condition was observed ($F(3,84) = 2.07$, $p = 0.111$). However, a significant main effect of group was identified ($F(1,28) = 15.90$, $p < 0.001$, $\eta^2p = 0.362$), indicating higher RMS activity in the CNSLBP group. The interaction effect was not significant ($F(3,84) = 1.07$, $p = 0.367$).

Zero-Crossing Rate (ZCR)

For the frontalis muscle, neither the main effect of condition nor group was significant. However, a significant condition × group interaction was observed ($F(3,84) = 2.91$, $p = 0.030$, $\eta^2p = 0.094$), indicating

different patterns of ZCR changes across conditions between groups.

For the corrugator supercilii muscle, no significant main or interaction effects were identified.

Table 4. Here

Table 5. Here

Heart Rate

No significant main effect of condition was observed for heart rate ($F(3,84) = 0.97$, $p = 0.411$, $\eta^2p = 0.033$). Similarly, neither the main effect of group ($F(1,28) = 1.47$, $p = 0.236$, $\eta^2p = 0.050$) nor the condition $\times$ group interaction ($F(3,84) = 1.34$, $p = 0.268$, $\eta^2p = 0.046$) was significant.

Discussion

The present study examined whether increasing cognitive workload elicited different subjective, behavioral, electromyographic, and cardiac responses in individuals with CNSLBP compared with healthy controls. The main finding was a dissociation between observable performance and physiological activation: participants with CNSLBP reported similar workload levels and achieved comparable behavioral performance, yet showed greater facial muscle electromyographic activity across task conditions. Increasing task demands also increased perceived workload and reduced performance, supporting the effectiveness of the workload manipulation.

This pattern suggests that individuals with CNSLBP may preserve task performance while requiring greater physiological effort. In practical terms, comparable productivity or similar self-reported workload should not necessarily be interpreted as comparable effort. The findings are consistent with resource allocation models in which persistent pain competes for limited cognitive resources and may increase the effort required to maintain performance under demand [8, 12]. Reliance on behavioral outcomes alone may therefore underestimate the actual workload experienced by individuals with chronic pain. The conceptual contribution of the present study is therefore not that individuals with CNSLBP performed worse under cognitive demand, but that they appeared to achieve comparable performance through greater physiological activation. This distinction is important for both clinical interpretation and occupational ergonomics, because hidden workload may accumulate over time even when short-term task performance remains preserved.

Increasing task demands resulted in significantly higher NASA-TLX scores and lower behavioral performance across participants, confirming the effectiveness of the workload manipulation. This finding is consistent with contemporary models of mental workload, which conceptualize workload as the cognitive cost associated with allocating limited attentional resources to meet task demands [8, 40]. Similarly, Ding et al. reported that increasing the difficulty of computer-based cognitive tasks was accompanied by higher subjective workload ratings and reduced task performance [40].

The observed decline in performance under more demanding conditions is also consistent with Multiple Resource Theory, which predicts performance deterioration when concurrent tasks compete for limited processing resources [12]. As cognitive demands increase, additional effort is required to maintain task execution, often resulting in reduced efficiency and poorer performance.

Interestingly, typing error rates remained relatively stable despite significant changes in workload and performance. This pattern suggests that participants adopted compensatory strategies to preserve accuracy under increasing cognitive demands. Similar findings have been reported in dual-task and occupational workload studies, where workload primarily affects response efficiency rather than response accuracy [5, 14].

Contrary to our initial expectations, no significant group differences were observed for NASA-TLX scores or behavioral performance. This finding should not be interpreted as evidence that cognitive workload is equivalent in both groups. Rather, it suggests that subjective ratings and behavioral outcomes may be insensitive to compensatory effort in this experimental context. Individuals with CNSLBP may have maintained performance by allocating additional resources that were captured more clearly by physiological measures than by self-report or typing performance.

To gain further insight into the mechanisms underlying task performance, physiological responses were examined alongside subjective and behavioral measures. In contrast to the relatively similar workload ratings and performance outcomes observed between groups, electromyographic measures provided evidence of differential physiological responses in participants with CNSLBP.

Facial electromyographic activity has been used as an indicator of mental effort, sustained attention, and task engagement [25, 55, 56]. In particular, activation of the corrugator supercilii has been associated with effortful information-processing and cognitive demand [56, 57]. The higher RMS activity observed in the CNSLBP group therefore supports the interpretation that maintaining performance may have required greater physiological effort.

A plausible explanation is that chronic pain functions as an additional background demand. Persistent pain may require ongoing monitoring, evaluation, and regulation, thereby consuming attentional resources that would otherwise be available for task performance [25]. From this perspective, individuals with chronic pain may operate with a reduced reserve of available cognitive resources and may therefore need to recruit additional physiological effort to perform cognitively demanding tasks at a level comparable to healthy individuals.

This interpretation is consistent with previous evidence suggesting that chronic pain is associated with alterations in attentional control and cognitive processing. Ge et al. reported that increasing cognitive load produced greater interference with motor performance in individuals with low back pain, indicating that pain-related processes may compete with task-related cognitive resources [58]. Similarly, contemporary neuroergonomic frameworks propose that physiological measures may capture

compensatory resource allocation processes that are not apparent from behavioral outcomes alone [7, 8].

Although conducted in a different chronic pain population, the present findings are also broadly consistent with those reported by Sjörs et al., who observed heightened physiological responses during mentally demanding tasks in individuals with chronic musculoskeletal pain [59]. Together, these findings support the notion that preserved behavioral performance does not necessarily imply equivalent cognitive efficiency. Rather, individuals with chronic pain may recruit additional physiological resources to compensate for the attentional and cognitive burden imposed by persistent pain.

The workload-related effects were more evident for RMS than for ZCR measures. RMS reflects the magnitude of muscle activation and has been widely used as an indicator of effort-related changes in muscular activity [55, 56]. In contrast, ZCR primarily reflects temporal characteristics of the EMG signal and motor unit firing behavior [60, 61]. The predominance of RMS effects in the present study suggests that the between-group differences were mainly reflected in the amplitude of facial muscle activation rather than in temporal features of the EMG signal.

Heart rate did not differ significantly across experimental conditions or between groups, and no condition $\times$ group interaction was observed. Thus, unlike the electromyographic measures, heart rate did not appear to be sensitive to either increasing task demands or group differences in the present study. This finding reinforces the value of a multimodal approach, as physiological measures may differ in their sensitivity to cognitive workload depending on the task and measurement characteristics.

The finding that individuals with CNSLBP maintained performance despite greater physiological activation has implications for computer-based and cognitively demanding work. In occupational settings, productivity metrics and self-reported workload may fail to detect increased physiological effort in workers with chronic pain. Such differences may be overlooked when workload assessment relies solely on short-term performance or self-reported measures.

Limitations and Future Directions

Several limitations should be considered when interpreting the findings. First, the sample size was relatively small, which may have limited statistical power to detect subtle effects, particularly for physiological outcomes. Second, participants were recruited from a university population and were predominantly young adults, which limits generalizability to broader clinical and occupational populations. Third, the study was conducted under controlled laboratory conditions using a simulated computer-based task; the findings may not fully reflect the complexity, duration, and psychosocial demands of real-world work.

Additional methodological limitations are also relevant. The physiological assessment focused on selected facial EMG and heart rate measures during a single experimental session. Facial EMG may reflect cognitive effort, but it is not specific to workload and may also be influenced by pain, affect,

concentration, and individual response tendencies. Heart rate was recorded using a consumer-grade wrist-worn device rather than electrocardiography, which may have limited the sensitivity and temporal precision of the cardiovascular assessment. Future studies should include larger and more clinically diverse samples, longer task durations, real or simulated occupational environments, and additional physiological and neurocognitive measures. Longitudinal studies are also needed to determine whether the greater physiological effort observed in CNSLBP contributes to fatigue, reduced work capacity, or other long-term occupational outcomes.

Conclusion

Increasing cognitive workload was associated with higher perceived workload and reduced task performance. Individuals with CNSLBP reported comparable workload levels and achieved similar behavioral performance to healthy controls, but showed greater facial electromyographic activity during task execution. These findings suggest that preserved performance in CNSLBP may require greater physiological effort. The study supports the value of combining physiological, behavioral, and subjective measures to better understand workload in chronic pain populations, particularly in computer-based and cognitively demanding work settings.

Declarations

Ethics Approval and consent to participate:

This study was conducted in accordance with the principles of the Declaration of Helsinki. It was approved by the Ethics Committee of the University of Social Welfare and Rehabilitation Sciences (code: IR.USWR.REC.1403.286). Written informed consent was obtained from all participants.

Consent for publication:

Not applicable

Competing interests:

The authors declare that they have no competing interests.

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Author Contribution

Z.R. contributed to the investigation, data collection, and preparation of the original draft. H.R.M. contributed to the conceptualization, methodology, supervision, data analysis, and critical revision of the manuscript. M.V. contributed to the statistical analysis and interpretation of the data. M.M. contributed to the interpretation of the findings and critical review and editing of the manuscript. All authors read and approved the final manuscript.

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Availability of data:

The datasets generated and/or analysed during the current study are available from the corresponding author (HRM) on reasonable request. The data are not publicly available due to privacy and ethical restrictions.

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