Overloaded and at Work: Investigating the Effect of Cognitive Workload on Assembly Task Performance

Francesco N. Biondi, University of Windsor, Ontario, Canada, and University of Utah, Salt Lake City, USA, **Angela Cacanindin**, **Caitlyn Douglas**, and **Joel Cort**, University of Windsor, Ontario, Canada

Objective: This study investigates the effect of cognitive overload on assembly task performance and muscle activity.

Background: Understanding an operator's cognitive workload is an important component in assessing human–machine interaction. However, little evidence is available on the effect that cognitive overload has on task performance and muscle activity when completing manufacturing tasks.

Method: Twenty-two volunteers completed an assembly task while performing a secondary cognitive task with increasing levels of demand (*n*-back). Performance in the assembly task (completion times, accuracy), muscle activity recorded as integrated electromyography (EMG), and self-reported workload were measured.

Results: Results show that the increasing cognitive demand imposed by the *n*-back task resulted in impaired assembly task performance, overall greater muscle activity, and higher self-reported workload.

Relative to the control condition, performing the 2-back task resulted in longer assembly task completion times (+10 s on average) and greater integrated EMG for flexor carpi ulnaris, triceps brachii, biceps brachii, anterior deltoid, and pectoralis major.

Conclusion: This study demonstrates that working under high cognitive load not only results in greater muscle activity, but also affects assembly task completion times, which may have a direct effect on manufacturing cycle times.

Application: Results are applicable to the assessment of the effects of high cognitive workload in manufacturing.

Keywords: cognitive workload, assembly task, multitasking, cognitive ergonomics, muscle activity

Address correspondence to Francesco N. Biondi, Department of Kinesiology, University of Windsor, 2555 College Ave, Winsdor, ON, Canada; e-mail: francesco.biondi@uwindsor.ca

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INTRODUCTION

Understanding cognitive workload and its effect on a system operator's performance is among the top challenges in human factors and ergonomics. It is clear that cognitive overload, that is the state of high cognitive workload (Gaillard, 2008), is detrimental to human performance and safety. Driving studies show that operating a vehicle while conducting taxing mental tasks renders the driver less attentive and increases crash risk (Biondi, Turrill et al., 2015; Harbluk et al., 2007; Owens et al., 2018). Research in healthcare also indicates that excessive cognitive workload experienced by healthcare professionals results in greater procedural failures and medication administration errors (Thomas et al., 2017).

In occupational ergonomics, the US National Occupational Research Agenda (NORA, 2018) notes that induced cognitive impairments have safety impact on the workforce. Nonoptimal levels of cognitive load resulting from mental fatigue or inattention can result in poor performance. It is also noted that the lack of attention toward the primary task at hand caused by concurrent distractions (i.e., using a cellphone or other technologies) might be a contributing factor of musculoskeletal symptoms (Toh et al., 2018). However, the specifics and dynamics of how cognitive overload alters an operator's performance, task completion, and injury risk in manufacturing are unclear.

Research conducted in office settings warns about the detrimental effect of cognitive overload on typing. Leyman et al. (2004) had participants type with or without completing a concurrent cognitive task. Subjective workload and typing performance were measured. Integrated electromyography (iEMG), which is the area under the curve of the rectified EMG signal, was adopted as a measure of muscle activity. Performing the two tasks concurrently resulted in higher self-reported workload and a 23% decrease in typing performance. In addition, an 11% increase in iEMG was found for the cervical erector spinae muscles under conditions of greater task demand. Iwanaga et al. (2000) investigated the effect of completing mental imagery tasks on muscle activation. iEMG was recorded for trapezius, biceps, and gastrocnemius muscles. A significant effect of secondary task was found on iEMG, with greater muscle activity found for all three muscles. Consistent results were found in Mazloum et al. (2008), where completing a cognitive task in addition to typing resulted in lower typing accuracy and longer completion times.

In manufacturing, cycle time is the time allocated to the human operator to complete a given job. A cycle time of 60 s, for example, implies that the operator has exactly 1 min to perform a specific series of tasks (like sourcing components from kits and assembling them), after which the exact same job needs to be repeated (Chen, 2013). Most research in cycle time management has traditionally focused on the technological aspects of manufacturing (e.g., machines, conveyors) with the goal of reducing cycle time by means of designing more efficient, less wasteful systems. HF/E research in human–system interaction, however, indicates that failure to account for the human component in system design has direct detrimental effects on task performance and safety (e.g., Biondi et al., 2019; Parasuraman, 2000; Shappell et al., 2007).

Experimental research on the effect of multitasking on human performance indicates that adding a secondary task to the task at hand increases overall cognitive load (Strayer et al., 2015), impairs performance for both the primary and secondary tasks (Owens et al., 2018), and, as suggested by Leyman et al. (2004) and Iwanaga et al. (2000), increases overall muscle activity. Yet, little is known about the effect of high cognitive workload on task performance and muscle activity in manufacturing. To address this, in this study we had participants perform an assembly task under increasing levels of cognitive load induced by the concurrent execution of the *n*-back task. The auditory *n*-back task (Mehler et al., 2011) is a widely adopted task in human factors literature and was chosen for its ability to impose constant and continuous levels of cognitive demand which are comparable to those of listening to the radio or conversing on a cell phone. Surface electromyogram (sEMG) was recorded and iEMG calculated for seven muscles on the forearm, arm, and chest. Completion time and accuracy in the assembly task, and self-reported workload were also measured.

We expect high cognitive workload to impair participants' ability to efficiently share attentional resources among the manufacturing and cognitive tasks. This will result in longer assembly task completion times, higher subjective workload, and, following Leyman et al. (2004) and Iwanaga et al.'s (2000) findings, overall greater muscle activity.

METHOD

Participants

Twenty-two volunteers (12 men, 10 women) were recruited from the University of Windsor. They had an age between 18 and 35 years, with a mean of 22 years. Participants with history of severe shoulder, elbow, wrist, hand, and lower back pain were excluded. This research complied with the American Psychological Association Code of Ethics and was approved by the Research Ethics Board at the University of Windsor (#19–065). Informed consent was obtained from each participant. Participants received a compensation of $10 for their participation in the experiment.

Design

The study design has a single independent variable, cognitive workload, which was manipulated by having participants perform the *n*-back task with three levels of difficulty: control (no *n*-back task), 0-back, and 2-back. Dependent measures were assembly task completion times and accuracy, integrated EMG, and self-reported workload using the NASA-TLX. Information on the equipment and data acquisitions and procedures is presented separately.

Equipment and Data Acquisition

Assembly task. The assembly task consisted of building a LEGO car set (kit #10707) of 20 individual parts. This task was chosen given its controllability and participants' familiarity with it (see Fast-Berglund et al., 2018, and Brolin, 2016, for a similar approach). Completion times and accuracy were measured. Completion time was calculated as the time difference between when participants were instructed to begin the assembly task (start time) and when they communicated to the research assistant that the task was completed (end time). Accuracy was calculated as the ratio between the number of correctly placed parts in each assembled LEGO set and the total number of parts ($n = 20$) in percentage. Five identical LEGO sets (one for each trial) were used in each experimental condition (more details are available in the procedure section).

Muscle activity. Seven channels of (sEMG were used to record the electric activity in the right arm of the following muscles: flexor carpi ulnaris (FCU), extensor carpi ulnaris (ECU), biceps brachii (BB), triceps brachii (TR), anterior deltoid (AD), posterior deltoid (PD), and pectoralis major (PM). Standardized locations were adopted for the positioning of the electrodes (Criswell, 2010). For each muscle, a pair of disposable surface electrodes (Medi-trace, Graphic Controls, Gananoque, ON, Canada) was placed along its line of action between the myotendinous junctions and innervation zones, with an inter-electrode distance of 3 cm. The sEMG signals were amplified using an eight-channel Bortec AMT-8 systems (gain = 1,000–5,000 Hz, input impedance = 10 GOhms, 10–1,000 Hz, CMRR 115 dB at 60 Hz, Bortec Biomedical, Calgary, AB, Canada), analog to digitally converted using a 16-bit A/D card (National Instruments, Austin, TX, USA) at a sampling rate of 2,048 Hz.

Self-reported workload. Self-reported workload was measured using the NASA-TLX scale (Hart & Staveland, 1988). It consists of six 10-point scales measuring mental workload, physical workload, temporal workload, effort, frustration, and performance.

n-Back. The auditory version of the *n*-back task (Mehler et al., 2011), which imposes increasing levels of memory demand, was used to manipulate cognitive task difficulty. In its 0-back and 2-back versions, it reproduces levels of cognitive load comparable to those experienced when performing everyday activities like radio listening or cellphone conversation. When completing this task, participants listened to a series of digits (randomized between zero and nine) presented at intervals of 3 s and were instructed to repeat aloud either the last (0-back) or the third-to-last (2-back) digit in the series. Audio files were downloaded from http://agelab.mit.edu/delayed-digit-recall-n-back-task.

Procedure

Upon entering the laboratory, participants completed an intake survey where they provided their demographics and information on past injuries. The familiarization phase then began. For the *n*-back, participants listened to an audio file with series of digits and were instructed to repeat aloud either the last digit (0-back) or the second to last digit presented in the series (2-back). Participants then familiarized themselves with the assembly task. They were given printed instructions on how to assemble the LEGO car and were asked to build the car as many times as needed until they felt comfortable building it without aids. All LEGO parts (total = 100, 20 parts per car × 5 cars) were divided by part type and placed in separate bins in front of the participant. Participants were instructed to source the part from the bins and assemble the LEGO parts consistently across all experimental trials. After familiarizing with the *n*-back and assembly tasks, we instrumented each participant with the sEMG electrodes. Maximum voluntary exertions (MVEs) for each muscle group being recorded were then collected. These MVEs were used to normalize the sEMG magnitudes collected during the experimental trials (Cort & Potvin, 2012). The MVEs were performed with the research assistant providing resistance against the movement. For the PM major and AD, the participant performed flexion of the arm against resistance placed on the upper extremity, whereas for the PD participants performed an arm extension. For the BB, the participants performed a bicep curl against resistance that will occur on a supinated wrist. The TR required a forearm extension against a resistance placed on the dorsal aspect of the wrist to collect this exertion. For the FCU and ECU, the participant attempted to flex and extend the wrist, respectively, against a resistance placed on the fingers to capture the MVE. Each of these maximal exertions were held for 2–3 seconds with a 60-s rest between each effort, with three sets for each muscle. Following the MVE protocol, participants rested for 5 min, during which their resting sEMG was collected.

The experimental phase lasted approximately 30 min. The three conditions whereby participants completed the assembly task concurrently with 0-back, 2-back, or control were counterbalanced across participants using a Latin square design. Each condition lasted approximately 5 min with participants taking as much time as they needed to complete each individual trial (completion times differed depending on individual differences and secondary task condition). During this time participants completed five identical LEGO sets (one LEGO set per trial). sEMG recording begun at the start of each of the three conditions and ended after all five trials were completed. Start and end times of each trial were flagged on the sEMG recording so that inter-trial recordings could be discarded and not analyzed further.

To minimize inter-trial time delays, we used five separate identical LEGO sets, one for each trial. At the beginning of each condition, all LEGO parts were divided by type in separate bins. To complete the assembly task, participants sourced the part from the bins and proceeded to assemble the set. At the end of each trial, the research assistant moved the completed LEGO set away from the participant, and the next trial began. At the end of each condition, we counted the number of correctly placed parts on the five LEGO sets to calculate task accuracy.

Completion times and accuracy for each trial were measured. After five trials were completed, participants completed the NASA-TLX, after which the next condition commenced.

Data Processing and Analysis

For the assembly task, completion times were averaged across five trials for each of the three conditions. Accuracy was calculated as the ratio between the number of correctly placed parts in the assembled LEGO sets and the total number of parts (n = 20) in percentage. Repeated-measures analysis of variance (ANOVA) with n-back condition as within-subject factor (control, 0-back, 2-back) was conducted on assembly task average completion times and accuracy.

Inter-trial sEMG recordings were removed from the analysis. sEMG recorded during each trial was conditioned by removing the DC bias, high-pass filtering at 140 Hz (6th order; Potvin & Brown, 2004; Staudenmann et al., 2007), rectifying, and then low-pass filtering at 1.5 Hz (6th order). The MVE sEMG data were furthered conditioned by applying a 2.5-s moving average filter and from this the peak sEMG amplitude was determined and considered the MVE for each muscle. Following this, the sEMG collected during the experimental trials were then normalized to each muscle MVE. Finally, for each muscle, iEMG (%MVE sec) was calculated. iEMG for the seven muscles was analyzed using repeated-measures ANOVA with n-back condition (three levels) as independent factor. For a description of the ANOVA and t-tests see Miller (1997).

For NASA-TLX, multiple repeated-measures ANOVA with n-back conditions (three levels) as within-subject factor and NASA-TLX scales as dependent measures were performed. Post hoc tests were conducted when significant main effects of conditions were found.

All statistical analyses were conducted using R project for statistical computing (R Core Team, 2008). Statistical alpha value was set to .05. Mauchly's tests were conducted to ascertain the distributions did not violate the assumption of sphericity. Parametric tests, repeated-measures ANOVA and t-tests, were conducted on parametric distributions.

RESULTS

Assembly Task Completion Times

A significant effect of condition was found, $F(2,42) = 3.71, p = .038$. Post hoc tests confirmed

TABLE 1: Average and Standard Error (*SE*) of Accuracy Across Control, 0-Back, and 2-Back Conditions

	Accuracy in %		
	Control	0-back	2-back
Average	88.14	87.54	87.82
SE	0.12	0.13	0.12

that, relative to the control condition, completing the assembly task under greater cognitive load imposed by the 2-back task resulted in longer completion times, $t(21) = 4.25$, $p = .017$, 95% CI [7.26, 12.7], Cohen's $d = .82$. No other significant differences were found.

Assembly Task Accuracy

Analyses revealed no significant difference in accuracy between the three conditions, $F(2.42) = .54$, $p = .56$. Average accuracy for the three conditions is presented in Table 1.

iEMG

Integrated EMG was analyzed to measure difference in total muscle activity over the duration of the assembly task. For iEMG, a significant main effect of condition was found for FCU, $F(2,42) = 3.76$, $p = .003$; TR, $F(2,42) = 5.46$, $p = .007$; BB, $F(2,42) = 6.51$, $p = .003$; PM, $F(2,42) = 4.08$, $p = .02$; PD, $F(2,42) = 5.98$, $p < .001$; and AD, $F(2,42) = 4.22$, $p = .02$. See Figure 1 for details.

Similar to the analysis on completion times, post hoc tests were run on iEMG collected in the control and 2-back conditions. Significant differences were found for triceps, $t(21) = 2.44$, $p < .05$, Cohen's $d = .16$; biceps, $t(21) = 2.66$, $p = .023$, Cohen's $d = .18$; posterior deltoids, $t(21) = 2.43$, $p = .024$, Cohen's $d = .11$; and anterior deltoids, $t(21) = 2.09$, $p = .004$, Cohen's $d = .10$, with greater iEMG found under conditions of greater cognitive load.

NASA-TLX

Relative to the control condition, performing the assembly task concurrently with the 2-back task resulted in greater ratings for mental workload, $t(21) = 13.81$, $p < .001$, physical workload, $t(21) = 2.38$, $p = .027$, temporal workload, $t(21) = 5.77$, $p < .001$, and frustration, $t(21) = 4.69$, $p < .001$. No significant differences were found between the control and 0-back conditions in Table 2.

DISCUSSION

Human factors research warns about the risk that completing multiple activities has on safety (Canada, 2019; NORA, 2018). However, little is known about the effect that multitasking has on human and task performance in manufacturing. For this reason, in this study we had participants complete an assembly task while concurrently

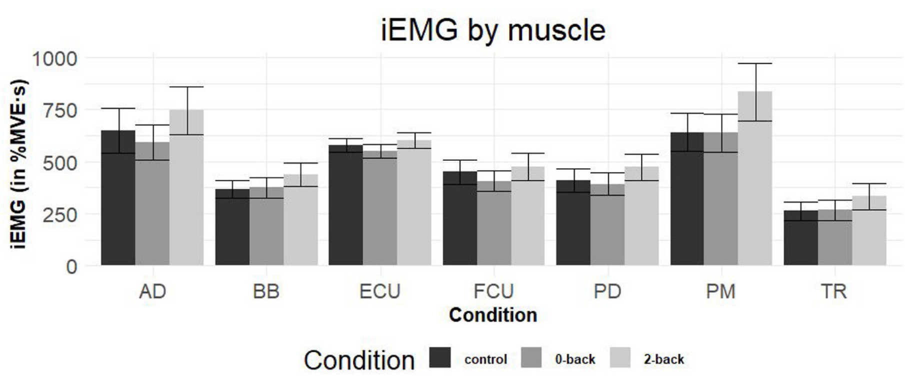

Figure 1. Average and standard deviation of integrated EMG (iEMG) for seven muscles across the three conditions.

TABLE 2: Average and Standard Error (*SE*) for NASA-TLX Ratings Across Experimental Conditions

	NASA-TLX Scale											
	Mental		Physical		Temporal		Success		Effort		Frustration	
Condition	Average	*SE*	Average	*SE*	Average	*SE*	Average	*SE*	Average	*SE*	Average	*SE*
Control	2.59	0.3	2.91	0.5	4.34	0.43	5.72	0.41	4.41	0.41	2.47	0.5
0-back	4.19	0.32	3.16	0.48	4.1	0.43	5.48	0.77	4.77	0.49	3	0.38
2-back	8.32	0.39	3.89	0.56	6.64	0.54	6.36	0.83	7.18	0.57	6.25	0.5

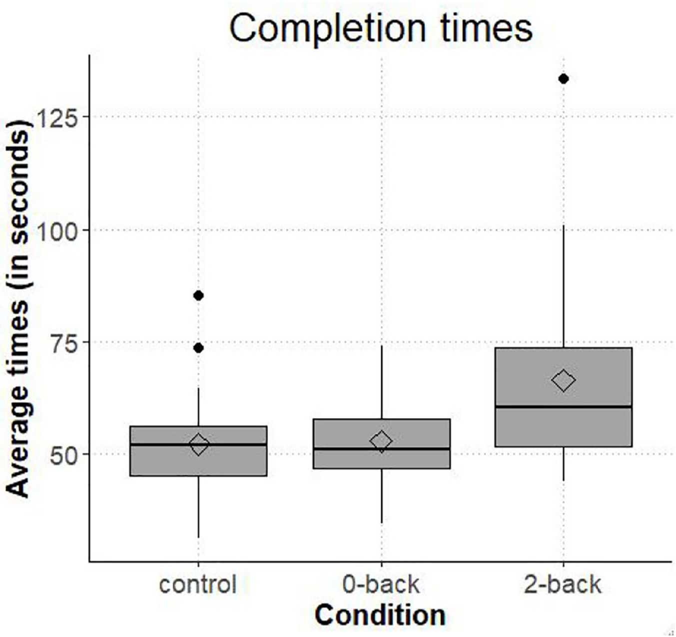

Figure 2. Boxplot with completion times across control, 0-back, and 2-back. Diamonds represent average completion times (in seconds). Lower, upper, and middle lines represent first and third quartiles, and median, respectively.

performing a mental activity with increasing levels of cognitive demand. Assembly task accuracy and completion times, self-reported workload, and muscle activity were measured.

Our results indicated that greater cognitive load resulted in longer assembly task completion times. While completing the assembly task in the control condition took approximately 50 s, performing the same task under greater cognitive load required an extra 10 s on average. A 50% increase in task completion times was even found for some participants (Figure 2). This finding is consistent with literature showing the negative impact of high cognitive workload on primary task performance and response times. In the studies by Biondi, Strayer, and colleagues, for example, greater driver cognitive workload induced by performing concurrent mental activities resulted in slower responses in a braking task (Rossi et al., 2012; Strayer et al., 2006) and overall lower driving accuracy (Biondi et al., 2015; Strayer & Drews, 2007).

The negative effect of cognitive overload on task completion times also has direct impact for scheduling, which is the practice of optimizing assembly task times in a manufacturing process (Kiran, 2019). While cycle times in manufacturing are designed to maximize production and efficiency, unanticipated interruptions in the assembling process due to system or human failures have direct consequences on production and costs. Our data clearly show that, although different cognitive workload did not affect task accuracy (possibly because of the relative simplicity of the task chosen), conditions of high cognitive load caused by excessive work demand or distraction are likely to increase completion times for assembly tasks.

High cognitive load experienced in the 2-back condition resulted in greater integrated EMG. This was found for FCU, triceps, biceps, pectorals, posterior deltoid, and anterior deltoid. In particular, relative to the control condition, iEMG increased by 25.46%, 17.80%, 14.61%, and 14.37% for triceps, biceps, posterior deltoid, and anterior deltoid, respectively. An increase in iEMG by 29% was found for pectorals. Combined with the longer task completion times found in the 2-back condition, these findings prove that high cognitive load not only slowed participants in the assembly task but, as a result, caused greater muscle activity over the duration of the longer task. Based on these results, we hypothesize that the high cognitive workload imposed by the concurrent mental task impaired participants' ability to efficiently allocate resources toward the assembly task, therefore resulting in poorer performance and greater muscle fatigue.

CONCLUSIONS

The National Safety Council warns about the increasing prevalence of distractions on the job (https://www.safetyandhealthmagazine.com/articles/distracted-on-the-job), and their risk on safety. Our study indicates that working while multitasking has a direct negative effect on muscle activity and task performance, with greater iEMG activity and longer task completion times found under condition of high cognitive workload.

It could be argued that the assembly task chosen in our study is not representative of traditional manufacturing tasks. However, research in occupational ergonomics in manufacturing has often adopted similar approaches when simulating factory jobs (Brolin, 2016; Fast-Berglund et al., 2018). Further, despite the *n*-back being a regimented, controlled task, it has successfully been adopted in human factors research to recreate the level of cognitive demand produced by real-world activities like cellphone or manual–vocal interface use (Harbluk et al., 2007; Mehler et al., 2011).

Future research will investigate the effect of cognitive workload in more naturalistic scenarios. Also, we will investigate the effect that working under conditions of cognitive overload has on force exertion and visual attention allocation during traditional manufacturing tasks.

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KEY POINTS

- The effect of cognitive overload on manufacturing tasks is investigated.
- Greater cognitive load induced by multitasking resulted in longer task completion times.
- Greater muscle activity was associated with greater cognitive load.
- Results are relevant for the assessment of manufacturing tasks.

ORCID iD

Francesco N. Biondi https://orcid.org/0000-0002-5558-4707

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Francesco N. Biondi, PhD, is an assistant professor at the Department of Kinesiology at the University of Windsor, and cofounder of the Human Systems Lab (hslab.org). He received his Master's degree in experimental psychology in 2011, and his Doctorate in experimental psychology in 2015 from the University of Padova, Italy. He holds academic appointments at the Department of Civil Engineering at the University of Windsor and at the Department of Psychology at the University of Utah.

Angela Cacanindin is an undergraduate student at the Department of Kinesiology at the University of Windsor.

Caitlyn Douglas received a Bachelor's degree in Human Kinetics from the Department of Kinesiology at the University of Windsor in 2019.

Joel Cort, PhD, is an associate professor at the Department of Kinesiology at the University of Windsor. He received his Master's degree in human kinetics from the University of Windsor in 2004, and his PhD in biomechanics from McMaster University in 2011.

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