Danger, high voltage!

Using EEG and EOG measurements for cognitive *over*load detection in a simulated industrial context

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ABSTRACT

Industrial settings will be characterized by far-reaching production automation brought about by advancements in robotics and artificial intelligence. As a consequence, human assembly workers will need to adapt quickly to new and more complex assembly procedures, which are most likely to increase cognitive workload, or potentially induce overload. Measurement and optimization protocols need to be developed in order to be able to monitor workers' cognitive load. Previous studies have used electroencephalographic (EEG, measuring brain activity) and electrooculographic (EOG, measuring eye movements) signals, using basic computer-based static tasks and without creating an experience of *over*load. In this study, EEG and EOG data was collected of 46 participants performing an ecologically valid assembly task while inducing three levels of cognitive load (low, high and overload). The lower individual alpha frequency (IAF) was identified as a promising marker for discriminating between different levels of cognitive load and overload.

1. Introduction

1.1. Cognitive load in assembly work

Industry 4.0 or "smart industry" is and will increasingly be characterized by wide-scale automation, connectivity and AI-driven technology, resulting in a manufacturing process that will become more and more efficient [19, 40, 41, 60]. Many jobs involving simple, repetitive tasks will increasingly be handed off to robots or–at the least–cobots (i.e., machines that physically interact with human workers) [45]. At the same time, it is expected that customer demand will push the industry towards increasing product variety to allow for broad product personalization, also coined "mass customization" [10, 67]. For example, in car manufacturing, it is more and more common for customers to have the ability to decide on certain design specifications. Amidst this evolution towards more customization stands the human assembly worker, who will need to operate in a more flexible and agile way, constantly adjusting his or her skills to changing job demands where automatization is not possible [47, 59, 80]. While this means assembly work in a manufacturing setting will become more challenging, human information processing capacities still remain limited. As a result, some workers will be unable to keep up with the ever increasing cognitive job demands [18, 80, 81]. From this perspective, it is highly important to work on measurement and optimization protocols to be able to first accurately measure and monitor workers' cognitive load, or more importantly cognitive *over*load.

Rooted in various seminal theoretical frameworks (cf., Sweller [66], Wickens [78]), cognitive load is generally defined as a multidimensional construct covering working memory processes, ranging from attention and perception to memory and decision making [70, 81]. Throughout the history of (cognitive) ergonomics, the construct of cognitive load played a crucial role in the prevention of occupational error, safety hazard, and negative (physical) stress caused by overload [10, 79, 81]. Measurement and optimization protocols are created to avoid or reduce this overload (e.g., through designing adaptive supporting interfaces, light-based guidance systems, or by (re)designing assemblies per se), maintaining optimal performance and well-being of workers [5, 9, 26, 43, 57, 65, 82].

Resonating with the multidimensional nature of the construct, the measurement of cognitive load encompasses the assessment of subjective perceptions, performance and physiological responses [14, 56, 70, 77, 81]. Whereas performance measures [8, 14] and self-report measures (e.g., NASA-TLX questionnaire based on Hart and Staveland [32]) for cognitive load assessment are widely used in industrial settings, important steps have to be made yet to arrive at a reliable and valid implementation of physiological measures [52, 68, 73]. Recent innovations and advancements in wearable technology have led to low-cost, easy-to-wear, and energy-efficient devices to measure, for example, skin conductance and heart rate at the wrist (e.g., Empatica E4, Chillband+) [21, 37] or electrical activity at the human scalp and around the eyes (e.g., Emotiv EPOC+, Muse, imec EEG headset, imec EOG glasses) [20, 55, 71, 72]. Because of these improvements in usability, efficiency and cost, it is expected that these devices will convince companies of their potential, making applied cognitive load measurement very prominent in the future [7, 24, 28, 33, 43]. Nevertheless, these devices will

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need to be wearable and unobtrusive, while guaranteeing a reliable, valid and sensitive monitoring of cognitive load in real-time [52].

1.2. Toward physiological cognitive load measurement during assembly work

In the fields of cognitive psychology and neuroscience, researchers have been studying the brain mechanisms and physiological correlates of cognitive load in detail for over 40 years (for a review, see [3, 12, 15]). Several physiological measures have been identified as markers of cognitive load, such as electrical activity of the brain as measured by electroencephalography (EEG) [3], eye blink metrics, pupil size and eye movement microsaccade magnitude [44, 49]. EEG measures are particularly interesting to the ergonomics and human factors field, due to technological advancements in mobile EEG-systems and dry electrode systems that do not require conductive gel [17, 54].

Especially appealing to applied research is spectral analysis of the EEG signal, since there is no need for trial repetitions or an explicit experimental paradigm. Specifically, the human EEG-signal consists of a sum of neural oscillations at different frequencies [6]. Spectral analysis decomposes the EEG signal into its different frequency components and computes power (reflecting amplitude of the oscillations) at each of these frequencies. Frequencies can then be binned into frequency bands, each of which has its functional significance, based on empirical research [3]. For example, high power in the traditional broad alpha frequency band (8 – 12 Hz) indicates a psychological state of relaxation. Therefore, alpha suppression (decreased power in the alpha band) is an important marker of cognitive load [3, 35, 42, 62, 63, 64].

If one distinguishes more narrow frequency bands in the alpha range, as preferred by Klimesch and colleagues [42], lower-frequency alpha bands (i.e., lower1 between 6–8 Hz and lower2 between 8–10 Hz) are more sensitive to general task demands (e.g., attentional processes or cognitive demands) and the upper-frequency alpha band (upper between 10–12 Hz) reflects more specific task demands (e.g., semantic memory processes or visuospatial factors) [22, 25, 27, 42, 64]. To a lesser degree, increased power in the theta frequency band (4-7 Hz) can also be related to high cognitive load [42].

Another physiological measure that is interesting for cognitive load monitoring at the workplace is EOG (i.e., electrooculography), which allows for eye blinks to be detected in a non-obtrusive way through mobile eye-tracking methods. Here, a reduced amount of blinks has been associated with high cognitive load, likely because the act of blinking is undesirable in this state, as it impedes visual information processing and the operator needs to stay concentrated [9, 46, 63, 74].

In general, only a small amount of studies deploying EEG or EOG measurements have tried to make the connection with cognitive load in a real-life industrial work context. Previous work mostly used very basic computerised tasks, in which for example mental calculations ([44] or memorization of digits and letters (cf., an n-back task in [38]) were used to experimentally induce different levels of cognitive load. By doing so, first, researchers were able to study the effect of cognitive load on isolated cognitive processes (attention, memory, executive control) while, secondly, keeping confounding variables under control. For example, motion artefacts, often related to muscle activity of the body and the face, can have a detrimental effect on the signal-to-noise ratio in physiological signals [48]. Altogether, these two criteria, covered by the bulk of previous research, are part of the crucial first steps towards measurement validation.

However, the next pivotal research steps need to translate these criteria for applied validation. First, although basic cognitive tasks are excellent to pinpoint isolated cognitive processes, they are not completely representative of the industrial tasks that the future flexible and agile industrial worker will need to perform. Second, confounding variables such as motion artefacts or ambient noise artefacts are inevitable in a real industrial work setting and preprocessing protocols to deal with them should be as efficient, practical and as limited as possible [29]. For these two reasons, more ecologically valid research is now highly needed to incrementally bridge the gap between highly controlled laboratory research and fully applied industrial cognitive load measurement.

Currently, there is some inspiring work available on using EEG and EOG to measure cognitive load with more ecologically valid tasks, but limited to seated operators performing robot-assisted surgery [31], driving a car [9] or, for example, working in an air traffic control room [4]. Less research is available for manufacturing contexts. The majority of studies in this area only investigated how to accurately question people about their cognitive load using self-report questionnaires and in-depth interviews. An important exception is a study by Kosch and colleagues [43], in which participants performed an assembly task (i.e., building constructions with Lego bricks) with two different assisting systems (i.e., paper instructions and in-situ projections indicating where a part needs to come). By looking at changes in the EEG frequency bands, they found indications that in-situ projections reduced working memory and cognitive load compared to paper instructions.

Hence, the current study wanted to take the next crucial step in applied measurement validation by, first, implementing a more ecologically valid task (requiring visuo-spatial information processing and information storage skills similar to performance on assembly tasks), while simulating a real-life industrial assembly context. Secondly, during execution of this task some motion with the hands and head was allowed in order to approach a more realistic (and hence practical) manufacturing scenario. To obtain high quality EEG data with a standard (not-wearable) EEG system, however, this study was still conducted in a controlled laboratory setting.

1.3. Addressing cognitive *over*load

Another aspect that has often been overlooked in measurement validation research, is empirically investigating the cognitive load 'redlines' or thresholds, namely cognitive *under*load and *over*load. According to the framework of Young and colleagues [81], cognitive overload arises when the incongruency between mental resources spent and the required task demands becomes too large. Some incongruency can be positive, challenging the worker to maintain performance levels and creating a potential state of flow (cf. flow theory, [13]), but a large incongruency can lead to a steep drop in performance and negative appraisals of the situation (e.g., threatening) [53, 79, 81]. In an overload state, the worker could be unable to cope with this incongruency, exhausting his or her cognitive effort supply, and enduring a subjective experience of emotional load (e.g., feelings of distress and frustration) [50, 70]. Extending previous work, the current study hence wants to make a clear distinction between an optimal state of high cognitive load, in which the worker is potentially challenged according to his or her level of skills, and a suboptimal state of cognitive overload, in which the task demands exceed the worker's mental resources and the worker is at risk of dropping out.

To this extent, a manual assembly task was chosen to create an overload condition (i.e., Tangram puzzle task, as described in [73]). Tangram puzzles are challenging dissection puzzles that consist of seven individual wooden pieces in different sizes and forms. The individual pieces should be put together in a certain way (without overlapping), in order to form a required shape represented in an example figure that is put in front of the participants. A pilot study was conducted in order to tune the difficulty levels of the task, as many possible shapes can be formed. As such, the difficulty of the puzzle can be manipulated by the extent to which individual pieces are recognizable in the example figure or if only contours (outlines) are shown. For example, in the overload condition, all puzzles have multiple touching sides, which makes it very difficult to find out how the puzzle should be arranged.

Participants were asked to solve these puzzles without knowing the difficulty level in advance and had to solve as many puzzles as possible within a specified time window (i.e., 10 minutes). In addition, overload was created by letting participants perform on a secondary task, (i.e., memorizing digits and pictures) with task-irrelevant factory sounds playing on the background. Taken together, the main goal of the present study was to explore whether physiological signals such as EEG and EOG can distinguish not only between a low and a high level of cognitive load, but also between a state of high load and overload.

2. Method

2.1. Participants

For this study, 46 participants between 19 and 40 years old (25 female, 21 male, $M_{age} = 25.8$, $SD_{age} = 4.19$) were recruited via an online questionnaire. There was a required variability in participants' educational background (ranging from secondary education to a PhD as highest degree) and visual-spatial intelligence. The latter was measured through an adapted version of the Revised Minnesota Paper Form Board Test [61]: only 20 of the total of 64 questions were included but they still covered the entire difficulty range. A time limit of 5 minutes was set and a correction for guessing (i.e., -1/4 for every incorrect answer) was applied. This research got the approval of the ethics committee of the University of Ghent.

2.2. Task

To make the study relatable to real-life assembly work, the task used in the conditions included both a motor component and an intellectual component: putting a puzzle together and remembering stimuli. The Tangram puzzle consisted of seven seperate wooden blocks with different geometrical shapes. Participants had 10 minutes in each condition to solve as many puzzles as possible. Based on an example figure of the presented puzzle printed on paper in front of them, the participant was required to recreate the puzzle correctly and as fast as possible. Three different conditions were presented, which were created to induce three different levels of cognitive load (i.e., low, high, and overload). This was done by adapting specific features of the task: (1) introducing different levels of difficulty of the task, (2) adding a supplementary working memory task, and (3) playing task-irrelevant noise.

First, to introduce different difficulty levels of the task, the image of the example figure printed on paper was manipulated. In the low load condition, the contours of each of the seven pieces of the Tangram puzzle were visible, making it quite easy to put the puzzle together. In the high load condition, the example figure of the puzzles consisted of 3 pairs of 2 pieces touching each other (with only the surrounding contour of the pair visible) and one separate piece, making it already harder to put these puzzles together. In the overload condition, all seven pieces of the example figure touched each other, which created only one surrounding contour. This made it very challenging to recreate the correct assembly as the separate pieces were not recognizable. It was expected that the majority of the participants would not succeed in solving many puzzles in the overload condition. In total, two different versions were created for each load condition (by randomizing the order of the puzzles), which were counterbalanced between participants. Participants were also asked about their previous experience with Tangram puzzles on a 7-point Likert scale. Most participants (67 percent) indicated to be rather inexperienced, while 11 percent of the participants chose the neutral option and 22 percent reported to have had some amount of experience with Tangram puzzles.

Second, to engage the participants' working memory, they were asked to remember visual stimuli while simultaneously performing the assembly task. After each load condition participants wrote down the stimuli they remembered. Two different kinds of stimuli were alternately presented: pictures representing a tool that is typically used in industry (e.g., a safety helmet, a conveyor belt, or a drilling machine) and a two-digit number. The number of stimuli that had to be remembered differed for each load condition: two pictures and two numbers in the low load condition, three pictures and three numbers in the high load condition and finally, five pictures and five numbers in the overload condition. In total, two different combinations were created for each load

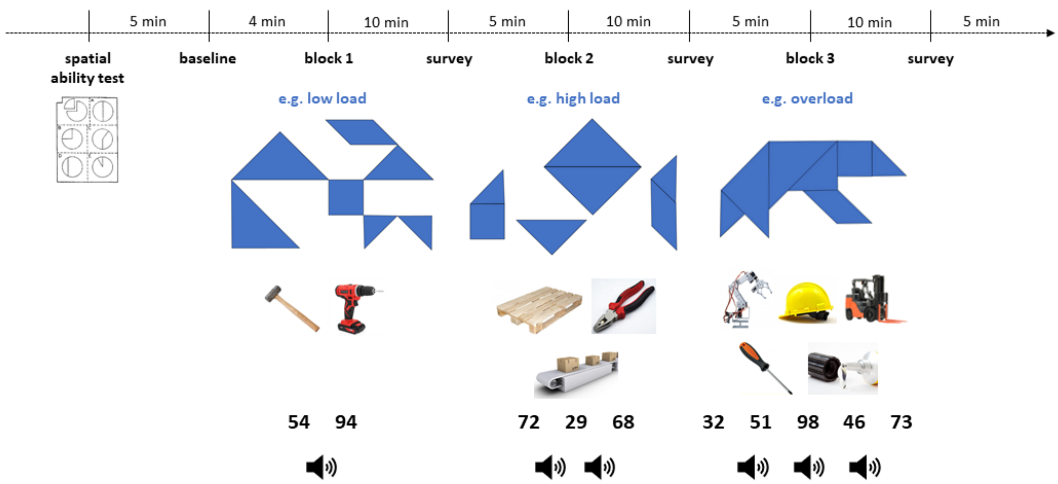

Figure 1: Design and procedure of the experiment. Order of load conditions is counterbalanced between participants (i.e., 6 possible orders).

condition (by randomizing the order of the visual stimuli), which were counterbalanced between participants.

Third, cognitive load was induced by presenting task-irrelevant auditory noise in the background. For generalization to real-life assembly work in an industrial setting, ambient factory floor sounds were played.

2.3. Research design and procedure

In this experiment, a within-subjects design was used in which each participant was exposed to each of the three experimental conditions (i.e., three levels of cognitive load: a low, high, and overload level). The length of each experimental condition was kept equal (i.e., 10 minutes) and a counterbalanced design, in which participants were attributed to one out of 6 possible orders (e.g., high - low - overload), was used to exclude possible learning effects and order effects.

First, the participant filled in the informed consent and performed a pretest measuring their spatial ability. Next, the testing equipment was prepared (i.e., EEG set, external electrodes on mastoids and around the eyes). After the set-up, each participant got detailed instructions about the experimental procedure and could try solving two puzzles in a test trial. Before starting the first experimental phase, a resting state measurement was conducted as a baseline. Participants were asked to relax, not move too much and avoid excessive eye movements. They were asked to keep their eyes open the first 2 minutes, and the close their eyes for the last 2 minutes. Next, the main experimental phase started, in which participants spent 10 minutes solving puzzles in each load condition. After each load condition there was a pause in which they completed a one-page questionnaire gauging experienced load, affective states, and memory of visual stimuli. The final step consisted of a participant debriefing and the clean-up. Figure 1 shows the experimental setting when performing the Tangram task.

2.4. Measurements

In the present experiment there were three types of outcomes for each load condition: the self-reported experience of cognitive load, task performance (Tangram puzzles and memory) and physiological measurements (EEG and EOG signals). Repeated measures ANOVA models were performed with load condition as a within subjects factor. Degrees of freedom were corrected using Greenhouse-Geisser estimates when Mauchly's test indicated that the assumption of sphericity had been violated, and partial eta squared effect sizes are reported. Pairwise comparisons between load conditions were conducted with holm-adjusted p values and Cohen's d effect sizes are reported.

Inspired on the NASA-TLX [32], Matthews et al. [50], and Van Acker et al. [69], cognitive load was gauged after every condition with a 7-point Likert scale ("I invested ... in the tasks I just completed"), ranging from very little mental effort to very much mental effort. Also stress and frustration levels were reported on a 7-point Likert scale ("While solving these tasks, I felt stressed / I felt frustrated"), ranging from totally disagree to totally agree. Finally, two constructs were inquired for the manipulation check on a 7-point Likert scale ranging from totally disagree to totally agree, being perceived task complexity ("The tasks were complex") and challenge

("I think the tasks were challenging"). Task performance was measured by looking at the number and percentage of correctly assembled puzzles and the percentage of remembered visual stimuli during the different load conditions.

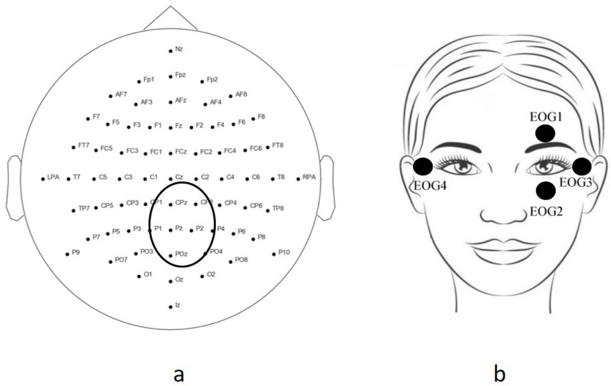

Figure 2: EEG (a) and EOG (b) channel locations.

With regard to physiological measurements, EEG and EOG signals were acquired with a Biosemi ActiveTwo measurement system (BioSemi, Amsterdam, Netherlands). EEG signals were obtained by using 64 scalp electrodes attached to a standard international 10–20 system cap (Figure 2a). Two additional external electrodes were attached to the left and right mastoids, which were used for offline re-referencing. EOG signals were collected through a bipolar channel of 2 external electrodes vertically positioned over the left eye (Figure 2b). EEG and EOG signals were both amplified and digitised with a sampling rate of 1024 Hz. Event triggers were sent for each condition through a serial port via the open-source application Psychopy [58].

EEG and EOG analysis was performed in Python with open-source Python software MNE and custom-made code [29]. The EEG data was preprocessed and normalised in order to eliminate confounding variables such as big movements or electrical noise, and to account for individual differences. Finally, down-sampling the data to 100 Hz was done to aid the processing speed of any further analysis. Two participants were eliminated because of technical issues and data loss during the experiment. For the spectral power analysis of the EEG data, three individual narrow alpha bands (lower1, lower2, and upper alpha) were created for every participant based on the local maximum in the eyes closed baseline condition. Average absolute alpha power was calculated for every experimental condition (averaged for a selection of relevant parietal electrodes: P1, P2, POz, CPz and Pz). Finally, the EOG data was also preprocessed and blink events were detected using MNE-based algorithms. The blink rate (count of blinks per minute) was calculated for every experimental condition. For a more detailed outline of this analysis you can access the data analysis description and scripts via this link `https://bit.ly/3lxTksI`.

3. Results

3.1. Self-reported experience

The self-reported experience of cognitive load was analyzed via a repeated measures ANOVA with the factor *load manipulation*. The analysis confirmed that the three load conditions significantly differed in reported mental investment, $F(1.70,76.41) = 104.21$, $p < .001$, $\eta p2 = .70$ (Figure 3). Controlling for gender, education level, age or spatial ability showed no statistically significant impact, all p's $> .05$. Post-hoc analysis revealed a significant difference of reported mental investment scores between low and high cognitive load $t = -8.99$, $p < .001$, $d = -1.33$, and high cognitive load and overload $t = -5.28$, $p < .001$, $d = -.78$. Similarly, the analysis for the experienced task complexity $F(2,90) = 262.87$, $p < .001$, $\eta p2 = .85$, and task challenge $F(2,90) = 114.49$, $p < .001$, $\eta p2 = .72$, also indicated that the task design succeeded in inducing three definite states of cognitive load. Consistently, participants reported a greater subjective experience of task complexity and challenge for the overload condition compared to the other load conditions. Finally, the results for the scale items inquiring stress, $F(1.27,77.43) = 55.01$, $p < .001$, $\eta p2 = .55$, and frustration, $F(2,90) = 95.33$, $p < .001$, $\eta p2 = .68$, also indicated that participants reported greater scores on these affective measures in the higher load conditions.

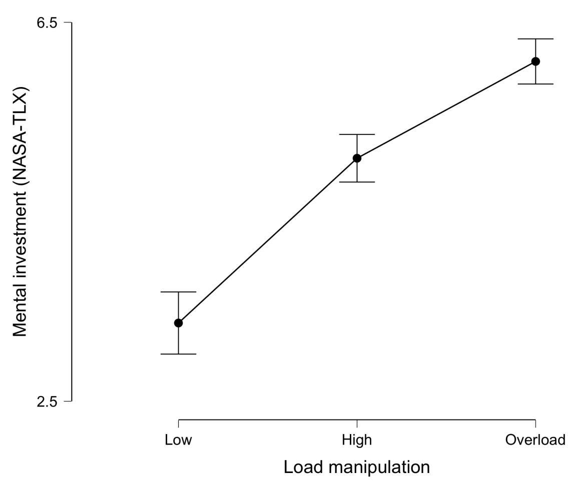

Figure 3: Mental investment score as a function of load manipulation. The more load, the more mental investment needed.

3.2. Task performance

The model also controlled for the statistically significant effect of spatial ability skills, $F(2,88) = 4.52$, $p = .01$, $\eta p2 = .09$. As expected, the number of correctly assembled puzzles significantly differed across load conditions, $F(2,88) = 581.23$, $p < .001$, $\eta p2 = .93$ (Figure 4). With increasing load, less puzzles were assembled correctly. During low, high and overload condition, participants correctly assembled respectively 33.13 ($SD = 6.84$), 12.11 ($SD = 7.80$) and 0.98 ($SD = 1.34$) Tangram puzzles on average. Controlling for gender, education level, or age showed no statistically significant impact, all p's $> .05$. Similarly, the proportion of remembered stimuli decreased with increasing cognitive load, $F(2,90) = 51.68$, $p < .001$, $\eta p2 = .54$. Participants remembered 89.67% of the visual stimuli ($SD = 18.69$) in the low load condition, 71.74% ($SD = 24.31$) in the high condition, and 50.65% ($SD = 22.45$) in the overload condition. Additional correlation analyses showed that the higher participants scored on the spatial intelligence test, $r = 0.47$, $p = 0.001$, the more puzzles they were able to solve. There was no relation between having experience with solving Tangram puzzles and task performance, $r = 0.14$, $p = 0.35$.

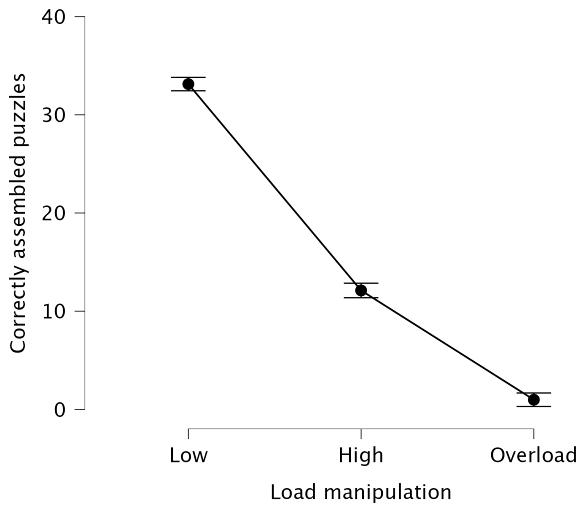

Figure 4: Number of correctly assembled puzzles as a function of load. The more load, the less puzzles were correctly solved.

3.3. Physiological measurements

3.3.1. EEG

A two-way repeated measures ANOVA was conducted to examine the effect of the *IAF band* (lower1, lower2, upper) and the *load manipulation* (low, high and overload) on average alpha activity. The main effects of *IAF band*, $F(1.16,50.03) = 44.35$, $p < .001$, $\eta p2 = .51$, and *load manipulation*, $F(2,86) = 8.73$, $p < .001$, $\eta p2 = .17$, were significant, as was their interaction effect, $F(2.53,108.56) = 6.60$, $p < .001$, $\eta p2 = .13$ (Figure 5). Post-hoc analysis revealed a significant difference between low and high cognitive load, and also between high cognitive load and overload, but only for the lower1 IAF. However, there was no significant difference for the lower2 and upper IAF between low and high cognitive load, nor between high cognitive load and overload (Table1). Controlling for gender, education level, age or spatial ability showed no statistically significant impact, all p's >.05.

3.3.2. EOG

With respect to blink rate, calculated as the number of blinks per minute, the model also controlled for the (marginally) statistically significant effect of spatial ability skills, $F(2,86) = 3.10$, $p = .05$, $\eta p2 = .07$. Still, significant differences between the load conditions were found, $F(2,86) = 20.48$, $p < .001$, $\eta p2 = .32$. During low, high and overload, participants blinked on average respectively 30.71 ($SD = 3.40$), 20.92 ($SD = 13.96$) and 19.16 ($SD = 12.32$) times, showing a decrease with increasing load (Figure 6). Post-hoc tests revealed less blinks per minute in the high load condition when compared to the low load condition, but not when comparing with the overload condition. Discriminating between high load and overload seems difficult with the feature blink rate (Table2). Controlling for gender, education level or age showed no statistically significant impact, all p's >.05.

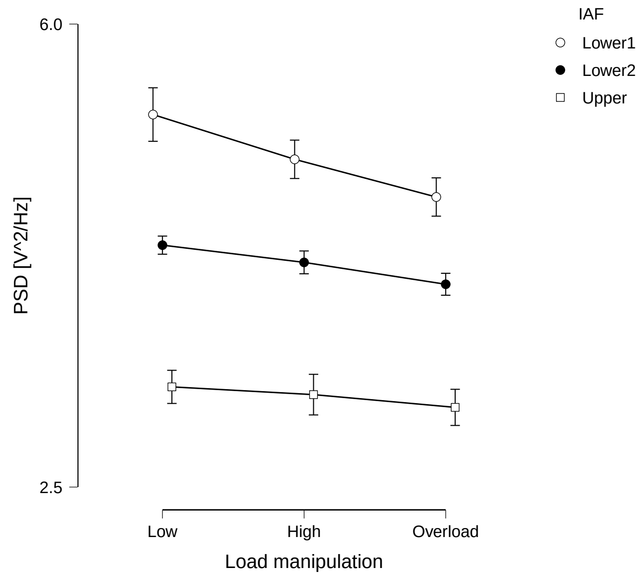

Figure 5: Individualized alpha power measured in power spectral density (V^2/Hz) split out for lower1 [IAF-4Hz, IAF-2Hz], lower2 [IAF-2Hz, IAF], and upper alpha [IAF, IAF+ 2Hz] as a function of load manipulation (error bars reflecting standard error). The mean IAF peak for all subjects was 10.06Hz (SD = 0.90Hz). Absolute alpha band power within these ranges was computed by averaging over the entire 10 minutes for every condition. The more load, the less alpha power could be observed.

Table 1
Post-hoc contrasts EEG

IAF	Load condition	t	df	p_{holm}	Cohen's d
lower1	low vs. high	2.85	43	.035	0.43
	high vs. overload	3.26	43	.012	0.49
lower2	low vs. high	1.38	43	.525	0.21
	high vs. overload	1.71	43	.376	0.26
upper	low vs. high	0.68	43	1.000	0.10
	high vs. overload	1.15	43	1.000	0.17

Table 2
Post-hoc contrasts EOG

Load condition	t	df	p_{holm}	Cohen's d
high vs. low	-4.64	43	.001	-0.69
high vs. overload	.92	43	.362	0.14

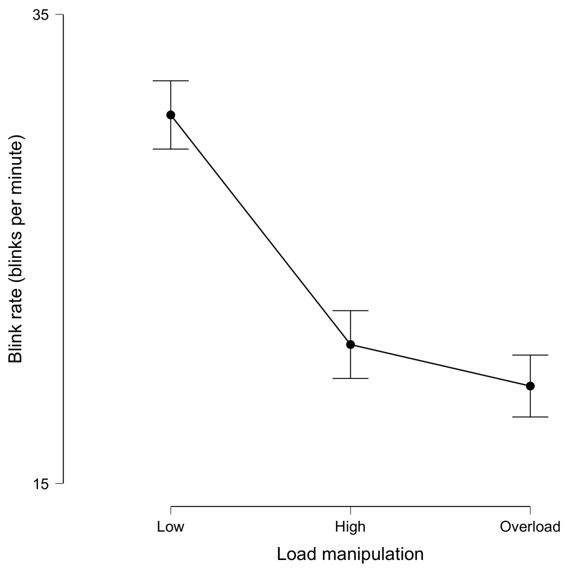

Figure 6: Blink rate (blinks per minute) as a function of load manipulation (error bars reflecting standard error). The more load, the less blinks could be observed.

3.3.3. Correlation analysis

The correlation analysis between all outcome measures (i.e., EEG, EOG, subjective and behavioral measures) revealed no statistically significant new insights. All results can be found in the link mentioned in the method section.

4. Discussion

With regard to cognitive ergonomics, it is most likely that assembly work in industrial settings will become cognitively challenging, increasing the need for human assembly workers to adapt quickly to new and more complex assembly procedures. More adaptation and complexity can increase the cognitive workload of the operator, who is often already under quite some time pressure and working in suboptimal conditions (e.g., environmental noise, distractions in surroundings), increasing the chances of also experiencing 'cognitive overload'. Although several studies have already tried to measure cognitive load with psychophysiological measures such as electroencephalographic (EEG, measuring brain activity) and electrooculographic (EOG, measuring eye movements) signals, the cognitive ergonomics of cognitive *over*load have been the subject of significantly less research efforts. In this study, the researchers therefore designed a lab experiment to collect EEG and EOG data of a large number of participants (N=46) performing an assembly task that was created to induce three levels of cognitive load (low load, high load and overload). In addition to using psychophysiological sensor data (EEG and EOG), performance metrics and subjective reports of experienced mental investment, task complexity, challenge, frustration and stress were also taken into account (and thus considering cognitive load as a multidimensional construct). The different levels of cognitive load were experimentally manipulated by creating different complexity levels in a dual task paradigm, which included Tangram puzzles and memorization tasks (i.e., remembering visual stimuli). This task was chosen to represent a typical 'assembly' (requiring visuo-spatial information processing and information storage skills similar to performance on assembly tasks in a manufacturing setting), as previous studies used more traditional paradigms with basic or static computerised tasks. Also, background stimuli (e.g. factory noises) were added to improve ecological validity.

4.1. Measuring overload

First, a manipulation check was performed to find out whether the conditions were able to successfully induce different levels of cognitive load and, most importantly, create an overload condition. An increase in cognitive load from low over high, to overload was reflected both in self-reported ratings of investment in mental resources and in the resulting task performance. The majority of the participants were not able to succeed in the dual task of the overload condition, as almost none of the puzzles were assembled and only half of the presented visual stimuli were remembered. Additionally, they reported greater experienced task complexity during this overload condition (i.e., almost 2 points higher than the high load condition, and very near to the most extreme part of the scale range), which was also reflected in higher levels of self-reported challenge, frustration and stress.

Second, the researchers were interested in whether specific EEG and EOG features could be used to successfully discriminate between (high) load and overload. More specifically, this study goes beyond the traditional approach of selecting fixed frequency bands in the frequency domain by investigating different bands of 'individualized alpha frequency' or IAF, resulting in detailed insights in specific frequency effects that are imperceptible when looking at the broad alpha range [22, 42]. The results showed clearly that this method of individualized alpha frequency can be used to differentiate between different levels of cognitive load and overload, especially when focusing on the *lower1* alpha power. This lower-frequency alpha band (i.e., approximately between 6–8 Hz) is reported to be more sensitive to general task demands (e.g., attentional processes or cognitive demands) [22, 25, 27, 42, 64]. Importantly, even though a difference in IAF was found between experimental load conditions, the small to medium effect sizes in the pairwise comparisons are in line with previous research that found the change in the alpha band frequency between different levels of cognitive load to be subtle [3, 11, 26, 39, 42, 43], particularly when compared to the difference between relaxation (or baseline activity) and effortful behavior (or experimental conditions).

Third, with regard to the EOG measurements, this study confirmed that blink rate can also be an efficient marker for differentiating between several levels of cognitive load. This is in line with previous studies showing that higher cognitive load leads to a decrease in blink rate [2, 9, 34, 46, 63, 74]. However, there was no significant difference with the in-between condition comparison of high load vs. overload.

This finding reiterates the conclusions of Ahmad and colleagues [2], who demonstrated that blink rate might not be sensitive enough to differentiate between more fine fluctuations in cognitive load.

4.2. Interpretation and implications

Hence, combining the psychophysiological findings, one can conclude that discriminating between a low and a high level of load (the way it has been in done in most previous research) is quite straightforward but discriminating between high load and overload is much more challenging, and the difference between the two in psychophysiological measures is very small (reflected in our small effect size for lower alpha activity, and no effect for EOG). Unfortunately, correlation analyses with the subjective and behavioral measures did not give us additional insights in this. However, a possible explanation is that feelings of despair and frustration could have made the participants give up along the way in the overload condition. Consequently, only a minimum of mental resources were invested and performance was not at the highest level when completing the task, due to a decrease in motivation [75, 76]. Indeed, some participants confirmed that the puzzles were too difficult and believed they were actually unsolvable, which was reflected in nervous laughs and freeze reactions (see behavioral accounts of cognitive overload; [1]). Giving up could mean a sharp decrease in cognitive load, although this is contrary to what was observed in the results for subjective reports, performance metrics or lower1 alpha EEG data. Interestingly enough, in the actual work context, these effects are likely reflected by dropout, bad product quality and errors because operators are becoming apathetic to their performance [51, 70]. To conclude, it is very hard to experimentally create a level of cognitive overload that comes close to the real-life experience. More research is needed to help draw the fine line between a suboptimal level of cognitive load (i.e., a very high level) and an overload state where the worker cannot deal with the situation anymore.

4.3. Limitations and future work

Although the researchers believe that this study is already a significant improvement in terms of ecological validity or generalizability to the real-life context (i.e., with a motor assembly task where participants needed to cope with the dual task paradigm and task-irrelevant noises), it is of course important to shift the research focus to workplace and industrial settings. Indeed, if this line of scrutiny wants to arrive at investigating 'cognition in the wild' [30], taking the step towards the so-called 'Evidence Readiness Level 8' [36], where findings are investigated and replicated in representative environments, is imperative. In the end, however, our findings were obtained in a controlled lab context, which represents a limitation to our study. Still, given the complexity of using electrophysiological measurement methods, and in our opinion lower signal quality of mobile devices, it is also important to first fully understand what can be measured in the controlled context of a lab. Our experiment was supposed to be an intermediate step to a fully ecologically valid field test in a manufacturing setting, but future work should include measurement setups that accommodate real assembly tasks (that require even more flexibility and multitasking) and mobile dry electrode and EOG systems. This way, more body movement is allowed, hence closing the gap even further. Future work could also focus on even more relevant assembly tasks or 3D-puzzles, and finding better ways for filtering out motion artefacts.

A second limitation of our study is that the conditions were relatively short time frames. Evidently, workers perform assemblies over longer time windows, so that cognitive fatigue effects or cognitive restoration might interact with cognitive load measurements. On the other hand, implementation in the field will require more fine-grained continuous indications of load levels, that is, addressing shorter time windows than 10 minutes. Also interpersonal differences in learning or personality (e.g., neuroticism) might affect load and overload over longer work time windows. The same goes for very specific contextual factors at the level of the work station or the assembly per se. Future work could therefore extend cross-sectional research with longer term repeated measures research accounting for intra-individual variations [23], caused by interpersonal differences or contextual factors. In doing so, such approaches can make the proposed cognitive load measurement protocol more robust, eventually tailoring protocols to the individual and contextual level, allowing for a more fine-grained reliable continuous measurement. In general, one could argue that using more than one physiological marker (i.e., a multidimensional approach) is beneficial for the detection and classification of different levels of cognitive load [15, 73]. In fact, machine learning algorithms that use the input from heart rate, eye-tracking and EEG sensors can lead to classification rates of around 90% [2]. Thus, future research that aims to distinguish between cognitive load and overload levels should incorporate an even wider sample of sensors.

The researchers think assessment via physiological signals is only one part of the equation. The current findings and the use of sensor data are useful for the first assessment or initial detection of overload. This way, work planners and manufacturing engineers can gain more thorough explanatory insights into the cognitive processes triggered by specific cognitive load antecedents such as task complexity, task switching, instruction formats, or for example, human-cobot communication [57, 65]. Equally, future smart manufacturing systems could automatically adapt production procedures or instructions to the level of cognitive load measured through real-time EEG and EOG. In so doing, the presentation of information and materials in the smart manufacturing environment can be redesigned, assemblies can be made more intuitive, or smart adaptive technologies such as AR-instructions or cobots can be implied to assist the operator in a more cognitively optimal way [16, 45, 47]. Optimizing cognitive load through smart measurement integration can hence foster employees' mental wellbeing and personal efficacy, eventually transforming the future operator into a flourishing knowledge worker. If not, cognitive overload caused by the very same smart manufacturing environment could contrarily lead to errors or safety hazards, or to detrimental effects on worker motivation and mental and physical health [18].

5. Conclusion

The results from the current study encourage the measurement and evaluation of EEG and EOG features for estimating cognitive (over)load in, at least, controlled lab settings allowing for more ecologically valid cognitive task demands and motion envelopes. The results from the current study validated lower alpha power activity as a promising marker for discriminating between high load and overload, while the EOG marker (i.e. blink rate) was not sensitive enough.

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