

Your Skin Resists: Exploring Electrodermal Activity as Workload Indicator during Manual Assembly

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ABSTRACT

Production lines are increasingly defined by smaller lot sizes that require workers to memorize frequent changes of assembly instructions. Previous research reports positive results of using assistive systems that compensate increments of workload by providing "just-in-time" instructions. However, there is rare evidence to which degree workload is alleviated by using assistive technologies. This work explores the potential of electrodermal activity (EDA) as a real-time monitoring tool for workload that is placed by two different assistive systems during manual assembly. In a preliminary user study (N=18), participants were induced with temporal and mental workload while conducting an assembly task with two different assistive systems: *paper instructions* and *in-situ projections*. Our preliminary findings indicate that EDA measures and working performance correlate to workload levels when using both assembly systems. Based on our results, we discuss future research in the area of smart factories that implicitly evaluate workload through EDA in real-time to adapt assistive technologies at workplaces individually during manual assembly.

ACM Classification Keywords

Human-centered computing: User studies

Author Keywords

Electrodermal Activity; Mental Workload; Temporal Demand; Assistive Systems; Workload-Aware Interfaces

INTRODUCTION AND BACKGROUND

Manual assembly at production lines is a cognitively demanding and stressful task. It does not rely on pure rote learning anymore as the manufacturing of individual end products has increased and product lot sizes have decreased [12]. This requires workers to memorize and adapt assembly instructions on-demand which potentially increases error rates and slows down the workers' performance. Switching between different instructions increases the workload as new assembly procedures need to be employed [16]. Assistive systems have been integrated at workplaces to cope with this increase in workload. For example, *in-situ projections* have been enrolled to



Figure 1. Participant assembling with *in-situ projections*. A wristband evaluates the worker's EDA magnitude that serves as an indicator for the current workload.

augment workplaces with contextual assistance [19]. Studies have shown a decrease in workload on self-rated scales [4, 9, 11] and objective measures [3, 10] that facilitate several physiological sensing devices when using *in-situ projections*. For example, electrodermal activity (EDA) has established itself as such a physiological measure to sense workload in real-time.

EDA describes the electrical conductance of skin that increases with physiological arousal and higher activity of sweat glands. Thus, EDA is often associated with task engagement [6], stress [17], and cognitive demand [15]. In contrary to previous physiological sensing modalities, EDA enables to sense workload using a non-intrusive wristband. Self-rated metrics, that have been used in past research to evaluate workload placed by assistive systems, do not provide real-time insights into cognitive states and are prone to subjective perception. In this work, we showcase how EDA provides an assessment of two different assembly instruction systems in terms of stress, cognitive workload, and working performance. We conducted an exploratory user study in which participants perform an assembly task using *paper instructions* and *in-situ projections* while being artificially induced with temporal and mental workload. We investigate differences in workload between *paper instructions* and *in-situ projections* while recording the assembly performance. Furthermore, we record EDA using a non-intrusive wristband (see Figure 1). We replicate, that

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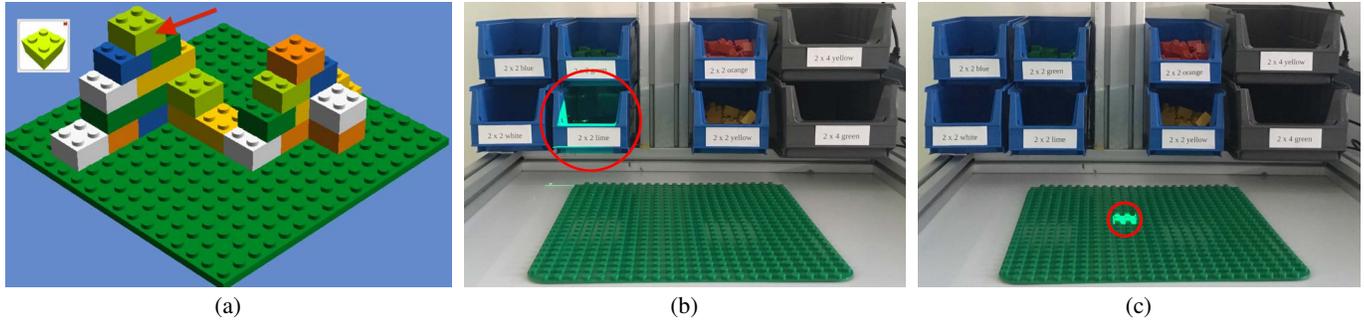


Figure 2. Used assembly instruction systems. (a): Printed *paper instruction*. (b): *In-situ projection* highlighting an item bin. (c): *In-situ projection* indicating where to put the Lego Duplo brick.

in-situ projections alleviate perceived temporal and mental workload compared to *paper instructions* according to assembly performance and subjectively perceived workload. We find, that our EDA measures converge with subjectively perceived workload and assess EDA as a potential real-time measure for workload during manual assembly. We discuss how future assistive systems can adaptively change instruction modalities to prevent frustration or boredom through cognitive overload and underload.

EXPLORATORY STUDY

We conducted a preliminary study to investigate differences in EDA, assembly performance, and subjective workload during assembly with *paper instructions* or *in-situ projections*. EDA is known to correlate positively when workload is utilized [17].

Assembly Instruction Systems

We use *paper instructions* and *in-situ projections* as assistive systems that have been presented by related work [5]. Participants were asked to assemble Lego Duplo bricks throughout the study. Lego Duplo has been frequently used in past research since the task complexity can be changed without changing the task itself [2, 5, 10]. We used six bricks with a 2×2 size placed in small item bins and two bricks with a 2×4 size placed in large item bins resulting in eight bricks of a different color. The overall number of assembly steps per condition comprised 24 working steps.

Paper Instructions

Paper instructions were printed single-sided on an A4 sheet of paper to ensure that the position and size of every step were the same. Instructions were put together using a folder and positioned to the preferred side of the user. The folded assembly instruction remained the same position during the study. The upper left corner shows the brick that has to be selected for the current step. A red arrow shows the final position of the brick (see Figure 2a).

In-Situ Projections

We use a projector mounted above the work table to display assembly steps on the working carrier. A Kinect v2 validates each item selection (see Figure 2b) as well as each assembly step (see Figure 2c) and proceeds to the next working step upon successful validation. This comprises the evaluation of correct item selection and assembly steps. If the user makes

an error the system waits with the current working step until it is done correctly.

Methodology and Procedure

We employ a within-subject design where we used the instruction systems, a time limit for temporal workload, and an addition task for cognitive workload as independent variables while participants simultaneously assemble a Lego Duplo construction. All conditions were counterbalanced across participants. We collect EDA throughout the study and label the data with the beginning and end of each condition. EDA is recorded using an Empatica E4¹.

Participants signed a consent form and provided their demographic data after we explained the course of research. We placed the Empatica E4 wristband on the non-dominant hand and asked the participants to keep this hand still to avoid noisy EDA measurements. After a five-minute resting phase, we started the recording process. First, we recorded EDA for one minute to obtain a baseline measurement. Afterwards, participants started the assembly task with *in-situ projections* or *paper instructions* with the respective secondary task. We describe the baseline measure and secondary task that induces stress and cognitive workload in the following.

Baseline

Participants were asked to relax for one minute while EDA was recorded. The recordings serve as a baseline measure for later analysis.

Plain Assembly

Participants were solely assembling Lego Duplo bricks using either (a) *in-situ projections* or (b) *paper instructions*.

Time Limit

In addition to the plain assembly, a time limit of one minute and thirty seconds was presented on a secondary screen next to the workspace. This intends to induce stress as participants were asked to complete their assembly task within the given time limit [13].

Addition Task

Parallel to the plain assembly, participants had to solve a math addition task. This is expected to strain working memory,

¹www.empatica.com/research/e4 - last access 2019-05-02

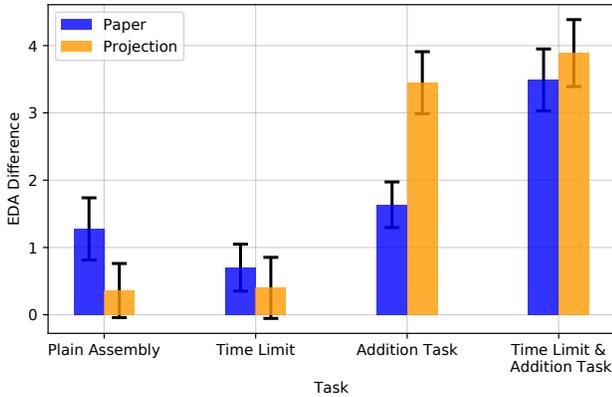


Figure 3. EDA Differences (EDAD) for each condition relative to the baseline. *In-situ projections* show a lower EDAD for an absent task difficulty or additional time limit. However, *paper instructions* show a lower EDAD when an addition task or a combination of addition tasks and time limits are introduced. The error bars depict the standard error.

which is a frequently used cognitive system regarding information retrieval and manipulation within short-term memory [15, 18]. The sum of two numbers, ranging between 0 – 9, had to be calculated. The experimenter verbally stated two random numbers after each working step. The participant had to calculate the sum and provide the solution orally before starting with the next working step.

Time Limit & Addition Task

A time limit and the addition task were employed at the same time.

Measures

Besides of EDA, we count the number of item selection errors and assembly errors. An item selection error is counted when participants pick a wrong brick. An assembly error was counted when the brick was not put on the final spot. We collect the subjective perception of workload using NASA-TLX questionnaires [7] after each condition.

Preliminary Results

We recruited 18 participants (aged between 22 - 29, 6 female) through university mailing lists. 16 participants were right-handed. All participants had normal or corrected-to-normal vision. Participants were compensated with ten Euro for their participation. We calculate the mean value of the EDA measurements for each condition across all participants to result with a single value per condition and participant. Afterward, we calculate the EDA Difference (EDAD) between the baseline measures and respective condition measures per participant [14]. By this, we normalize individual differences in EDA measures.

We submitted the EDAD measures to a Bayesian Repeated Measures ANOVA [8] which includes the assembly instruction modality (i.e., *paper instruction* and *in-situ projection*), cognitive workload (i.e., addition task), and temporal demand (i.e., time limit) as independent variables to quantify differences in objectively perceived workload. By analyzing the

Table 1. Mean number of item selection errors for each condition. The lowest values are bold.

Task Difficulty	Paper	Projection
Plain Assembly	0.167	0.111
Time Limit	0.278	0.278
Addition Task	0.556	0.056
Time Limit & Addition Task	0.111	0.000

Table 2. Mean number of assembly errors for each condition. The lowest values are bold.

Task Difficulty	Paper	Projection
Plain Assembly	0.167	0.333
Time Limit	0.167	0.333
Addition Task	0.667	0.500
Time Limit & Addition Task	0.167	0.222

EDAD measures, we found a Bayes Factor (BF_{10}) of 13.08 when manipulating cognitive resources by adding an addition task to the assembly. This means that a difference in EDAD measures is 13.08 times more likely to occur when adding a cognitive task during assembly, regardless of the instruction system. Combining the assembly instruction system and a cognitively demanding task resulted in a Bayes Factor of 2.09. Combining temporal demand and cognitive workload for both assembly instruction systems yielded a Bayes Factor of 2.51. The Bayes Factor of the remaining variables indicated a low probability of differentiating from each other ($BF_{10} < 1$ and $BF_{10} > -1$).

Furthermore, we submitted the raw NASA-TLX scores to a Bayesian Repeated Measures ANOVA. Again, we found a Bayes Factor (BF_{10}) of 8.60 when adding an addition task during assembly. Combining the assembly instruction systems and the addition task resulted in a Bayes Factor of 7.73 while a combination of temporal demand and cognitive workload resulted in a Bayes Factor of 9.81, regardless of the used assembly instruction system. The Bayes Factor of the remaining variables indicated a low probability of differentiating from each other ($BF_{10} < 1$ and $BF_{10} > -1$).

We descriptively analyze our data to find differences between the single conditions. *Paper instructions* without task elicited a larger EDAD ($M = 1.276, SD = 0.462$) compared to *in-situ projections* ($M = 0.360, SD = 0.402$). *Paper instructions* also showed a larger EDAD when adding a time limit ($M = 0.7, SD = 0.345$) compared to *in-situ projections* ($M = 0.4, SD = 0.454$). However, *in-situ projections* showed a larger EDAD during addition tasks ($M = 3.448, SD = 0.46$) compared to *paper instructions*, ($M = 1.635, SD = 0.339$). Finally, we find a larger EDAD for *in-situ projections* when combining the time limit and addition task ($M = 3.888, SD = 0.497$) compared to *paper instructions* ($M = 3.49, SD = 0.46$). Figure 3 visualizes the mean EDADs for each condition. In average, participants made ($M = 0.285, SD = 0.77$) errors when using *paper instructions* and ($M = 0.229, SD = 0.851$) errors when using *in-situ projections*. Table 1 shows the average number

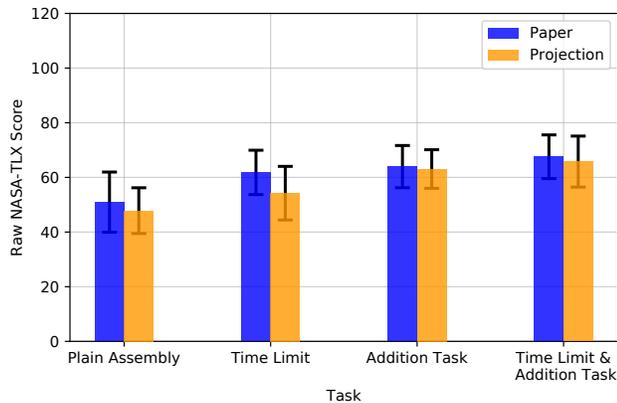


Figure 4. Raw NASA-TLX scores for each condition. The error bars indicate the standard error.

of item selection errors and Table 2 shows the average number of assembly errors. The raw NASA-TLX scores reveal, that *in-situ projections* cause less subjective workload than *paper instructions* during all tasks (see Figure 4).

DISCUSSION

We discuss the implications from the results of our pilot study in the following.

EDAD and Assembly Performance

We find that *in-situ projections* without additional tasks improve the assembly performance regarding the number of errors and subjectively perceived workload compared to *paper instructions*. Thus, we can confirm the outcomes of previous work [5]. Furthermore, we find profound differences in EDADs between *paper instructions* and *in-situ instructions*. While *in-situ projections* provided lower EDADs during plain assembly and conditions including a time limit, we find larger EDADs during conditions that include an addition task. However, the subjective perception of workload was still higher for *paper instructions* although the EDADs for *in-situ projections* were higher. Also, the overall number of item selection and assembly errors for the addition task was lower *in-situ projections*. We believe that this effect is due to task engagement which is known to correlate positively with EDA [6, 15]. Such real-time insight into EDADs and assembly performance could serve as a context-aware detector for boredom, task engagement, or frustration. Another reason could be that flipping the current page during *paper instructions* provided a short mental break from the addition task, thus resulting in lower EDADs during assembly with *paper instructions*.

Using the Right Instruction for the Right Job

Real-time adaptation of assembly instructions can be used to elicit desired physical and mental states. If a high number of assembly errors in combination with high EDADs during the use of *in-situ projections* are measured, an adaptive system advises the worker to take a break or recommend physical *paper instructions* as an alternative. This analysis can be used for reinforcement learning, where changes in the environment are registered (e.g., worker switched to paper instructions

which result in fewer errors) to tailor assembly instructions to the individual level of workload.

Limitations and Future Work

Participants were instructed to use their dominant hand for the whole assembly procedure to avoid noisy EDA measures from their non-dominant hand. In future work, we will evaluate a multimodal set of non-intrusive stationary sensors for workload detection [1] including our mobile approach. Before this, we will conduct qualitative inquiries with workers to gather requirements for real-time workload management during manual assembly.

CONCLUSION

In this work, we explore Electrodermal Activity (EDA) as an objective measure for workload during manual assembly tasks with two different instruction systems. Through the incorporation of time limits and addition tasks in parallel, we evaluate to which degree workload is perceived by *paper instructions* and *in-situ projections*. We find that an evaluation of item selection and assembly errors in combination with EDA resembles an alternative for robust workload detection. We believe that a combination of environmental and physiological data can be used in the future to design adaptive workload-aware assembly instruction systems at workplaces that reduce boredom and frustration.

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