Working with Augmented Reality?: A Long-Term Analysis of In-Situ Instructions at the Assembly Workplace

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Working with Augmented Reality? A Long-Term Analysis of In-Situ Instructions at the Assembly Workplace

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ABSTRACT
Due to increasing complexity of products and the demographic change at manual assembly workplaces, interactive and context-aware instructions for assembling products are becoming more and more important. Over the last years, many systems using head-mounted displays (HMDs) and in-situ projection have been proposed. We are observing a trend in assistive systems using in-situ projection for supporting workers during work tasks. Recent advances in technology enable robust detection of almost every work step, which is done at workplaces. With this improvement in robustness, a continuous usage of assistive systems at the workplace becomes possible. In this work, we provide results of a long-term study in an industrial workplace with an overall runtime of 11 full workdays. In our study, each participant assembled at least three full workdays using in-situ projected instructions. We separately considered two different user groups comprising expert and untrained workers. Our results show a decrease in performance for expert workers and a learning success for untrained workers.

Author Keywords
In-situ projection; Augmented Reality; assistive technology; long-term evaluation

ACM Classification Keywords
H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous

INTRODUCTION
With increasing ability to seamlessly interconnect sensors, many production processes are augmented with sensor technology. This mainly enables to track products from design along their way through the manufacturing processes [27].

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Figure 1. A user is working on an interactive workplace. A projector is displaying in-situ instructions directly on the work piece while a Kinect_v2 checks for correct assembly.

Additionally, this enables to create a better quality documentation for each assembled product. Today, the quality documentation is mostly done by taking a picture of the assembly process after each work step. This is helpful if an assembly error in assembled products was noticed after shipping them to customers. In such cases, companies need to recall all erroneous products. However, instead of recalling every product of the erroneous type, the pictures taken during the assembly can be used to identify erroneous parts in a post-process and are helping to only recall the products, where an error was made. Moreover, in the near future, we can easily imagine using more sensor data than just an RGB image to automatically store the parameters of production (e.g. the used tools and parts, the assembly duration, the applied force by a drill) in a database. These data could be used to automatically identify assembly errors and even prevent them from happening in the first place.

In addition to just using the stored data of the assembly steps for quality control, the stored data can also be used to assist workers during their assembly tasks. An assistive system could automatically detect when a worker made a mistake or forgot a work step during the assembly and intervene immediately. These systems could be used in several scenarios: training *new workers* in a new assembly task, continuously supporting *expert workers* by only intervening if an error was made, and continuously supporting cognitively *disabled workers*, who benefit from a constant assistance [14, 15].

As augmenting users or workplaces to provide assistance during work tasks has been a research topic for more than 20 years [6], many assistive systems for Industrial Augmented Reality for providing help in each task from designing to assembling a product have been proposed [8, 9]. Although many approaches have been considered, only a few made it out of the lab into the industry [26]. According to Navab [24], all approaches that might make it to market have to fulfill three requirements: An assistive system has to be reliable, user-friendly, and scalable. Recently, we can recognize a trend that systems using in-situ projection (e.g. see Figure 1) to assist users at their workplace are more and more deployed in workplaces in the industry and are even already commercially available. One example is the Werklicht system from EXTEND3D[1], which uses laser projection to highlight drilling positions. Another example is the Light Guide System from OPS solutions[2]. Finally, we can observe that systems using in-situ projection fulfill Navab's [24] requirements and are likely to become more present in the market soon.

We believe that this trend will sustain, as instructions on an HMD were not well accepted by the users [30]. Surprisingly, the long-term effects of in-situ projected instructions on workers have not been scientifically studied yet. With this work, we aim to close this gap and provide insights considering disadvantages and benefits of a long-term usage of in-situ projected instructions at the workplace for *untrained workers* and *expert workers*. To the best of the authors' knowledge, this is the first work to provide a long-term evaluation of in-situ instructions at manual assembly workplaces including 3 days of assembling using in-situ instructions.

The contribution of the paper is two-fold: (1) We present a continuation of an assistive system using in-situ instructions and work step detection, which works robust enough to perform a long-term study with a duration of 11 days. (2) We provide results of a long-term usage of in-situ instructions at manual assembly workplaces considering two different user groups: *expert workers* and *untrained workers*.

RELATED WORK

Industrial Augmented Reality, which is applying Augmented Reality (AR) in industrial processes, was first intoduced in 1992, when Caudell and Miezell [6] suggested using instructions that are shown on an HMD to support workers during assembly processes. In their manufacturing scenario, the HMD is showing the drill positions and information about the drilling distance in a textual representation. Later, Boud et al. [4] compared AR and Virtual Reality (VR) instructions to traditional 2D drawings and found, that interactive instructions outperform traditional ones. However, manufacturing is only one of many scenarios for Industrial Augmented Reality (IAR), as comprehensive surveys [25, 26] show, that IAR can be used to support almost every aspect of a product life cycle. Fite-Georgel [8] divided IAR into five areas of application: product design, manufacturing, commissioning, maintenance, and decommissioning. While our work focuses on the manufacturing scenario, we mostly analyze related work associated with manufacturing.

Many systems for providing assembly instructions on different types of displays have been proposed. While Billinghurst et al. [2] use mobile phones to give AR instructions, Echtler et al. [7] use a display mounted directly on a welding gun to provide information about the position of welding spots. In their work, they are using a tracking system integrated into the work environment to track the position of the welding gun at all times. Thereby, it is possible to show exact welding positions to workers on a display. Moreover, Gavish et al. [16] compare tablet-based AR instructions to interactive VR instructions. They found that AR and VR training requires a longer Task Completion Time (TCT) than video-based training. A chest-worn display (CWD) is used by Sakata et al. [29] as they compared it to an HMD in a remote collaboration assembly scenario. In a user study, they found that the CWD is more suitable for the task compared to the HMD.

Other work in AR manufacturing can be assigned to two main categories: presenting instructions on HMDs and presenting instructions in-situ, i.e. projecting directly at the workplace. Considering the HMDs, Tang et al. [31] showed that overlaying the assembly workplace with AR instructions using an HMD reduces the error rate in assembly tasks by 82% compared to paper-based instructions, instructions on a monitor, or instructions that are steadily displayed on an HMD. Henderson and Feiner [20] used an HMD to display instructions for maintenance tasks. They were using the HMD in the study for approximately 75 minutes. More recently, Zheng et al. [33] provided further research towards finding the optimal position for displaying feedback on an HMD. In their study, they compared providing instructions using a central position on the HMD, which is directly in the user's field of view against a peripheral position, a hand-held tablet representation, and printed instructions. Their results reveal that a central HMD representation is faster than the peripheral representation. Further, they did not find a difference in completion time between the HMD and non-HMD approaches.

Other systems focused on projecting content directly onto the workplace. Early versions of in-situ projections were presented in 2003 by Sakata et al. [28]. They introduced a wearable active camera/laser-pointer that a remote expert can control to provide assembly help. With increasing technology, an assistive system using a top-mounted projector and a top-mounted camera was introduced by Bannat et al. [1]. Their system projects pictorial instructions directly in the worker's field of view. The system of Korn et al. [21] also uses pictorial in-situ instructions for assembling Lego cars. Kosch et al. [22] experimented with different error feedback modalities for assistive systems. Recently, Funk et al. [14] presented in-situ instructions for the workplace by projecting the contour

[1]EXTEND3D - http://www.extend3d.de/werklichtpro.php (last access 03-10-17)
[2]OPS solutions - http://www.ops-solutions.com (last access 03-10-17)

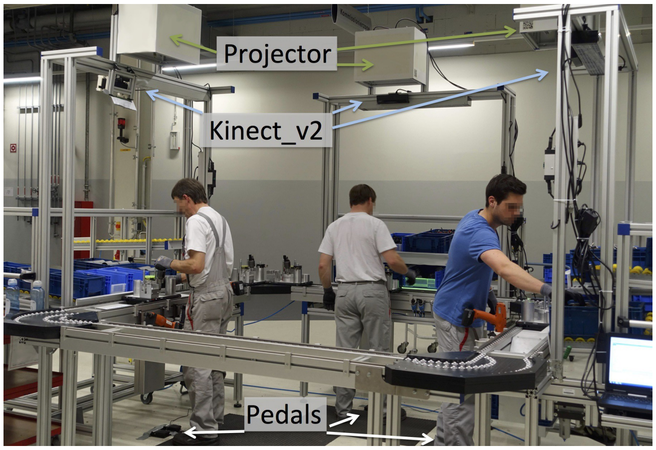


Figure 2. We equipped an assembly line consisting of three workplaces with our context-aware assistive system for providing in-situ assembly instructions. Each workplace is equipped with a Kinect_v2 depth camera and a projector. Work steps, which are too small to be detected with the camera, can be proceeded manually using foot pedals.

of assembly parts. Their study had an overall run time of approximately 60 minutes. They also found that in-situ instructions are superior to other feedback systems e.g. HMDs [13] using the GATM benchmark [11]. In another study, Büttner et al. [5] confirmed these results. Moreover, Marner et al. [23] compared in-situ projected instructions to instructions that are shown on a screen. They conclude that in-situ instructions are faster and lead to fewer errors.

Long-term evaluations of head-mounted displays have so far only been conducted in an order picking scenario. For example, Schwerdtfeger et al. [30] were testing an approach similar to the attention funnel by Biocca et al. [3] in a two hours study to get insights about long-term usage of AR in production environments. Their results show that using a paper-based baseline, workers made more picking errors and were slightly slower than using a HMD. However, after using the HMD for two hours participants reported headaches, problems to focus on the instructions on the HMD, and needed a 15-minute break from the HMD. Grubert et al. [17] report another long-term evaluation of order picking processes with a four-hour duration. They could reproduce the findings of Schwerdtfeger et al. Moreover, Tumler et al. [32] analyzed the physical effects of long-term usage of an HMD in an order-picking scenario. However, they could not find a difference in the users' strain between HMD and traditional paper picking.

To sum up, related work investigated various approaches for providing instructions for work tasks. Thereby, mostly head-mounted displays and in-situ projection approaches were used. In order picking scenarios, studies lasting from two to four hours using an HMD revealed problems being accepted by the users, as they complained about headaches and problems to focus. However, projection-based systems have not been studied for longer than approximately one hour, yet. In this work, we want to evaluate the long-term effects of using in-situ projected instructions for at least one work day in industrial assembly scenarios. Thereby, we want to provide an in-depth analysis considering the different user-groups that are involved in industrial assembly.

DIFFERENT USER GROUPS

Workers that are employed for industrial manufacturing tasks can be assigned to one of the following two groups:

Expert workers: There are many *expert workers*, who are employed by companies for several years. Usually, these workers are performing the assembly tasks for many years and know every detail about the assembly task and every possible source of errors.

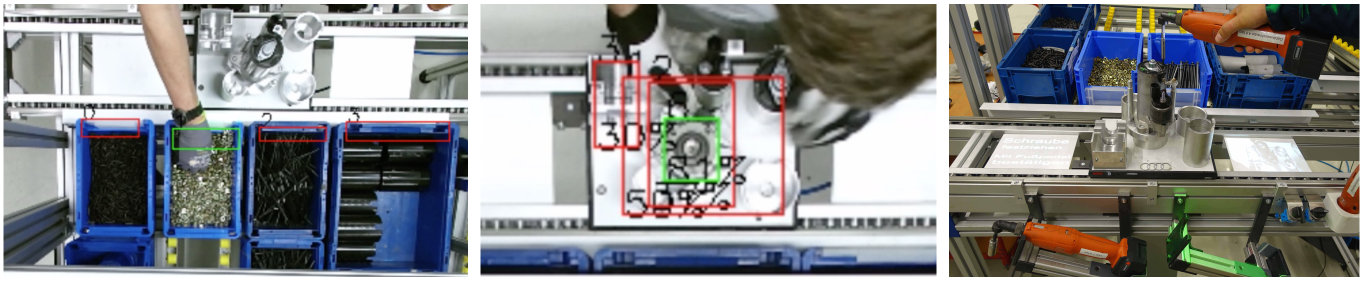
Untrained workers: By *untrained workers*, we refer to workers who have assembly experience, but are not familiar with assembling a specific product. According to a survey of the German Socio-Economic Panel [18], only 5.72% of the workers that were employed from 1999 to 2011 had a low qualification. Especially nowadays, where a mismatch in skills and jobs lead to a skills shortage[3], the number of *untrained workers* will increase. Moreover, we are currently experiencing a trend that companies are employing more and more temporary workers. These workers usually get a contract that lasts only up to 6 weeks. As the temporary workers are not familiar with the work tasks of the new company, the number of untrained workers in companies increased over the last years. Usually, these *untrained workers* are trained for the task they need to work on (mostly by an *expert worker*).

SYSTEM

We introduce an assistive system, which provides context-aware instructions using in-situ projection to give feedback to workers during assembly tasks directly. The presented system is a continuation of the system presented by Funk et al. [14]. The system can automatically advance projected feedback when a correct assembly step was performed or when a worker picked a correct part from the boxes containing the spare parts. Our system consists of three main components (see Figure 2): a top-mounted Kinect_v2 depth camera that can detect work steps at the workplace, a top-mounted projector that can project in-situ feedback directly at the position where the assembly is performed, and a foot pedal that enables the worker to manually switch the feedback if for a work step the depth camera cannot detect the changes robustly. As the system only uses components that need to be mounted over and under the workplace, our system can be added to almost every manual assembly workplace that can be found in the industry. Usually, a workplace consists of a fixed assembly area where workers perform assembly steps, a spare part area where boxes are storing the parts that are used for the assembly, and a tool area where tools that are used during the assembly are stored.

To detect when a worker picks a correct part, our system implements a pick-detection. Therefore, the locations of the boxes to be visually marked in a calibration step once using a rectangle in the camera image of the top-mounted Kinect_v2 (see Figure 3a). The observed area over a box has a height of 15cm, a length of 5cm and a variable width matching the

[3]BBC news (last access 03-10-17) - http://www.bbc.com/news/business-34297368



(a) (b) (c)

Figure 3. An overview of the different features of the prototype. Our assistive system is capable of (a) detecting when a user pics a part from a box by observing the depth data of the Kinect_v2 above the boxes (b) detecting correct assembly using the depth data, and (c) providing in-situ feedback using a top-mounted projector.

used boxes' width. Upon defining the box, the system captures the depth data and stores a mean depth value of the observed area. Once the area is created, the system compares the current mean depth values with 30 frames per second to the stored values. If the worker is picking a part from the box, the picking results in a change of the depth values in the observed area. To achieve a robust pick-detection, we compare each depth value inside the box's rectangle to the mean depth value that was stored with the observed area. If the change in the value is above a threshold of 5mm and within the area's height of 15cm, we consider the pixel as changed. If 40% of the pixels are considered changed, the system detects a pick (see Figure 3a - green rectangle) otherwise, the system does not detect a pick. The percentage of pixels that need to be detected to trigger a pick can be adjusted to the size of the workers' hands. For workers with smaller hands, a value of 35% is also sufficient.

For detecting when a worker assembled a part correctly at the assembly area, we implemented an assembly detection. Therefore, a user has to teach the depth data of a correctly assembled product to the system in an initial calibration step for each assembly step. The user has to assemble a part correctly and then visually mark the position of the assembly using a rectangle (see Figure 3b). Thereby, the system stores the depth data of the correctly assembled workpiece. After the depth data of the correct assembly was stored, the system continuously compares the stored depth data to the current depth data inside the area in the rectangle. Thereby, each pixel is compared to the stored pixel. A pixel is considered matching if it is within a range of +3mm and -3mm. If at least 80% of the pixels inside the rectangle are considered matching, the system triggers a correct assembly of the part (see Figure 3b - green rectangle). Otherwise, the system shows a red rectangle and does not trigger the next work step. The threshold of 80% was determined empirically and was providing a good accuracy for the used tasks. When choosing a higher threshold, a better accuracy can be achieved, however, if the threshold is too high a correctly assembled part might not be detected anymore because of noise in the sensor. With our system, we are able to robustly detect the assembly of parts that are 1cm$\times$1cm$\times$1cm. Parts that are smaller, cannot be detected accurately in the distance of 1.6m above the assembly area using a Kinect_v2 due to its resolution and noise in the sensor. Therefore, we included a foot pedal (see Figure 2) with two buttons that enables the worker to advance the feedback of the system forward and backward in case the assembled part is too small to be detected automatically.

Our assistive system is further able to create workflows that consist of multiple work steps. For example, a work step could be picking a part from a box. In that case, the box is highlighted using a green light. If the work step is assembling a picked part, the system highlights the position where the part has to be assembled using a contour representation of the part, which has to be assembled (c.f. [10]). If a part has to be removed the part is blinking green. We refrained from using a red color as red usually indicates that an error was made. In case the system is detecting that a worker picks a part from a wrong box, the system highlights the wrong box with a red light for 2.5 seconds. In an initial calibration step, the administrator needs to define the order of the work steps once by defining a so-called workflow. If a workflow reached the last step, the system restarts the workflow from the beginning after waiting 5 seconds.

A STUDY WITH EXPERT AND UNTRAINED WORKERS

We evaluate the long-term effects of in-situ instructions at the assembly workplace for *expert workers* and *untrained workers*. Therefore, we set up our system at the factory buildings of a major car manufacturing company, where we assembled cars' engine starters. We conducted two experiments, which follow the same experiment design. The only difference between the experiments were the participants: *expert workers* and *untrained workers*.

Design

We considered a repeated measures design with the availability of in-situ instructions as the only independent variable. As dependent variables, we were measuring the TCT, the number of errors, and the NASA-TLX [19]. We did not counterbalance the order of the conditions, as we wanted to measure the initial effect of the in-situ instructions on a worker. The experiment setup is constructed on an assembly line. Thus, the errors and TCT are measured for the whole group of three workers.

Apparatus and Setup

For the study, we equipped the three workplaces of a U-shaped assembly line with our assistive system (see Figure 2). The assembly line is used to produce cars' engine starters and was deployed at a major car manufacturing company. We especially created the assembly line for conducting this study. The way of assembling the engine starters using a U-shaped assembly line differs from the assembly process that the car manufacturing company uses to assemble the engine starters. We deliberately introduced a new assembly line to create a new setting for both *expert workers* and *untrained workers*. Further, we designed a new workpiece carrier, which holds the assembled product during assembly. It was designed in a way that every performed work step can be seen by the top-mounted Kinect_v2

The assembly line consists of a roller conveyor on which workpiece carriers can be transferred between the workplaces. For the study, we used seven workpiece carriers that can be transferred between the workplaces on the U-shaped assembly line (see Figure 2). The transferring of the workpiece carriers has to be done manually. In the study, the workpiece carriers were transferred between the workplaces counterclockwise. At each workplace, a pneumatic clamp was firmly mounting the workpiece carrier at the exact same position that the Kinect_v2 is able to perform the assembly detection.

The three workplaces are part of one assembly line to assemble engine starters. Therefore, the workplaces are dependent on each other. We divided the tasks that are performed at each workplace in a way that workers need the same amount of time at each workplace. For workplace 1 (WP1), the task consisted of 18 work steps: twelve could be automatically detected, six had to be advanced manually, because the parts were too small. Workplace 2 (WP2) consisted of twelve work steps, thereby three had to be advanced manually, and nine were detected automatically. Finally, workplace 3 (WP3) consisted of fourteen work steps: four had to be advanced manually and ten were detected automatically. However, if one worker needs more time, the next worker in line needs to wait for the previous workplace to finish. To introduce a buffer in case a workplace needs more time than usual, we use seven workpiece carriers at the assembly line.

Procedure

As we conducted the study at a car manufacturing company, we had to stick to the company's breaks and hours of work. Thus, a workday consisted of four slots: from 7.45am till 8.45am, from 9am till 11.45am, from 12.30pm till 1.45pm, and from 2pm to 3pm. Accordingly, one workday consists of assembling 360 minutes, which is exactly 6 hours per day. As the workers should learn the whole assembly process on each of the three workplaces (WP1, WP2, WP3), all workers had to work on each of the three assembly workplaces in the assembly line. We iterated the workplaces in a counter-clockwise way after each break, resulting in iterating 4 times per workday. As the assembly line is built in a U-shape, after the final step was performed at WP3, a study assistant removed the assembled engine starter from the workpiece carrier, put it into a container, and counted the produced starters. Afterwards, the assistant moved the empty workpiece carrier in reach of WP1 again. The errors were counted in a post-assembly quality control. Thereby a quality inspector checked the engine starters for assembly errors. After three days of assembling, we conducted a group interview where we invited the participants and asked them for their opinion about using in-situ instructions at the workplace. To measure the learning effect, we then assembled the car's engine starter using the same assembly line for 3 days without using instructions. We started with the procedure with the group of *untrained workers* and then repeated the procedure for the *expert workers*. However, due to time limitations of the car manufacturing company, we had only two instead of three days for the condition assembling without instructions with the *expert workers*. This results in a study run time of 11 workdays.

Participants

We recruited 3 expert workers and 3 untrained workers (all male), who all are employees of a major car manufacturing company. The expert workers were on average 43.34 years old (*SD* = 4.49 years) and the untrained workers were on average 45.67 years old (*SD* = 12.65 years). All expert workers had over a year of experience in assembling the engine starter. The untrained workers had experience in working on assembly tasks but did not assemble an engine starter before. All workers were not familiar with the workpiece carrier and the U-shaped assembly line as it was especially designed for this experiment.

Ethical clearance for conducting this study was provided by the German Federal Ministry for Economic Affairs and Energy and the industrial council of the car manufacturing company, where we conducted the study. Further, all participants gave written consent to volunteer in participating in this study.

Quantitative Results

We report the results of the study for both *expert workers* and *untrained workers* separately. For both user groups, we statistically compared the TCT, number of errors, and NASA-TLX between the two conditions using a one-way ANOVA.

Expert Workers

Considering the TCT, the *expert workers* were faster without instructions with an average of 74.03s (*SD* = 11.63s) per produced part compared to during the learning phase using in-situ instructions, which resulted in an average of 109.40s (*SD* = 31.96). The ANOVA revealed a significant difference between the approaches $F(1, 6) = 8.428$, $p = .027$. The effect size shows a large effect ($\eta^2 = .584$). A graphical representation is depicted in Figure 4.

When comparing the NASA-TLX between the two conditions, the average NASA-TLX score for the *expert workers* was 74.34 (*SD* = 12.25) using the in-situ instructions and 72.67 (*SD* = 4.98) without instructions. A statistical comparison using an ANOVA test did not reveal a significant difference between the conditions ($p > .05$). A graphical representation of the average TLX scores is depicted in Figure 5.

As the assembly errors that were made during the study were determined in a post-process, only descriptive statistics can be reported for the number of errors. However, the *expert workers* did not make any assembly errors both with and without the in-situ instructions.

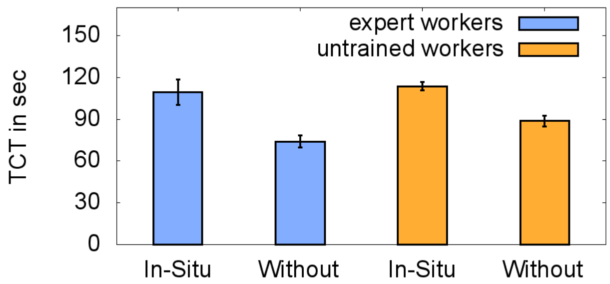


Figure 4. The average time per produced part for expert workers and untrained workers using in-situ instructions and assembling without instructions. Error bars depict the standard error.

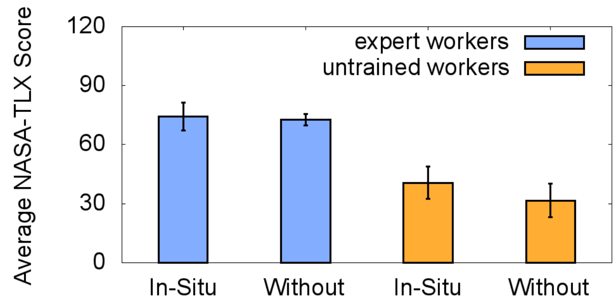


Figure 5. The average NASA-TLX score using in-situ instructions and assembling without instructions. Error bars depict the standard error.

Untrained Workers

When considering the average time to produce a part, the *untrained workers* were faster after the learning phase without using instructions with an average of 88.65s (SD = 12.41s) compared to 113.62s (SD = 10.14s) during the learning phase using in-situ instructions. The ANOVA revealed a significant difference between the conditions $F(1,10) = 23.621$, $p = .001$. The effect size estimate shows a large effect ($\eta^2 = .703$). The results are depicted in Figure 4.

The post-process analysis of errors revealed that the group of *untrained workers* made 5 errors while working with the in-situ instructions. When afterwards working without the instructions, they did not make any assembly errors.

We further compared the NASA-TLX between the two conditions for the *untrained workers*. Using the in-situ instructions, the questionnaire resulted in an average score of 40.67 (SD = 14.34) and an average score of 31.67 (SD = 14.70) without instructions. A statistical comparison using the ANOVA did not reveal a significant difference between the conditions ($p > .05$). A graphical representation of the average TLX scores is depicted in Figure 5.

Between User-Groups

Considering *expert workers* and *untrained workers* as different user groups, we statistically compare the results as a between groups experiment. We use a one-way ANOVA to compare the TCT, number of errors, and TLX score when using in-situ instructions and assembling without instructions afterwards.

When comparing the TCT for assembling the engine starter while using in-situ instructions, the ANOVA did not find a significant difference between the *expert workers* and the *untrained workers* ($p > .05$). However, when comparing the TCT for assembling the engine starter without using instructions, the ANOVA found a significant difference between the *expert workers* and the *untrained workers* $F(1,6) = 6.589$, $p = .043$. The effect size estimate shows a large effect ($\eta^2 = .523$).

We further compared the average NASA-TLX score between the *expert workers* and *untrained workers*. However, the ANOVA test did not reveal a significant difference for using the in-situ instructions ($p > .05$) and for assembling without instructions ($p > .05$).

Qualitative Results

For better understanding the effects of the in-situ instructions on both worker groups, we provide detailed results from the interviews that were conducted after each condition. Thereby P1-P3 are from the *untrained workers* group and P4-P6 are *expert workers*.

Participants disliked that the workplaces that were used in the study differed from the workplaces they were used to. Especially that the workplace constructed for the study was designed in a U-shape as *"[they] had to wait for the previous worker to finish"* (P2). However, after working with the in-situ instructions for a longer time, a participant stated that *"[he] got used to the system"* (P1). One participant told us that *"working with the in-situ instructions was relaxing"* (P3). On the other hand, participants perceived the in-situ instructions as *"an additional task, which required [them] to pay extra attention to the colors"* (i.e. not causing red error feedback). Sometimes participants also were *"irritated because of the triggered red light"* (P5) that indicated a wrong pick. Using the in-situ instructions while working was perceived as *"working twice as much"* (P2) because *"manually advancing the instructions with the foot pedal lead to a higher load on the left foot"* (P6). On the other hand, the workers liked that they were supported during their tasks because *"the system shows us how the order of the work steps has to be performed"* (P1). However, one participant stated that *"[he] felt like a robot"* (P6). Overall, most participants stated that *"[they] wouldn't want to work with the system every day"* but it *"would be great to learn new tasks with the system."*

DISCUSSION

Considering the *expert workers*, assembling with in-situ instructions resulted in a significantly higher TCT than assembling without instructions. The workers told us in the interviews that this was mainly because the in-situ instructions were distracting them. However, regarding the perceived cognitive workload that was measured with the NASA-TLX, we could not detect a significant difference between using in-situ instructions and assembling without instructions. Another explanation for the better performance without the in-situ instructions could be that we used the in-situ instructions as the first condition to learn the task. After assembling three days with the in-situ instructions, the *expert workers* might have also gotten used to the new assembly line.

As we did not counterbalance the order of the conditions and used the in-situ projection condition to teach the assembly, we can see that after using the in-situ instructions for three days, the *untrained workers* were able to assemble the product significantly faster and without making any error. The workers told us that at first, the system was very helpful for them to learn the assembly steps. However, they told us that after assembling with the in-situ instructions for a while, they were distracted by the instructions. Therefore, we believe that the time that *untrained workers* were using the in-situ instructions to learn how to assemble the engine starter was too long. Regarding the NASA-TLX score, we could not find a significant difference between the approaches. Informed by the *untrained workers*' answers in the interviews, we believe that a learning an assembly task using in-situ instructions is a good alternative to traditional ways of learning. However, finding the right duration of using in-situ instructions in order to learn a task has not been found yet. This could be an interesting problem to investigate in future work.

When comparing the NASA-TLX score of *expert workers* and *untrained workers*, we found that the *expert workers* perceived a higher cognitive workload for both using in-situ instructions and assembling without instruction compared to the *untrained workers*. We believe that this is because the *expert workers* were used assemble the engine starters in a single assembly workplace. As for the study we especially built an assembly line, it might cause waiting times for the other workers. We believe that this newly introduced dependency had an influence on the perceived cognitive workload of the *expert workers*.

From the experiment with *untrained workers*, we learned that in-situ projected instructions could transfer knowledge about the new workflow to the workers. However, using in-situ instructions for too long might result in slowing down the worker. We believe that including a better adaptiveness of the instructions that focuses on the current skill of the worker would improve the system. We believe that there has to be a point in time where assistance for *untrained workers* is not beneficial anymore. Finding this point in time could be interesting for future work.

To sum up the findings for the *expert workers* and the *untrained workers*, the in-situ instructions slowed them down in their work. However, the qualitative statements indicate that the *untrained workers* liked learning work steps using the in-situ projection of our assistive system.

CONCLUSION

In this work, we analyzed the long-term effects of context-aware in-situ instructions on two different groups of workers that can be found in the industry: *expert workers* and *untrained workers*. We deployed our assistive system using in-situ projection in an assembly hall. Through user studies in an industrial setting, we provide results of assembling with in-situ instructions. During the study, each participant assembled at least three full work days using in-situ projected instructions. To the best of the authors' knowledge, this is the first study exploring such long-term effects.

The results indicate that for *untrained workers*, in-situ instructions are useful during the learning phase. In our study, the *untrained workers* could assemble products significantly faster and without making errors after 3 days of learning the assembly task using in-situ projection. However, while learning the assembly task, the in-situ instructions slow the workers down in their assembly speed. We especially can see this effect for the *expert workers*, who already know the assembly task. As for the *expert workers*, the in-situ instructions slow down the Task Completion Time and increase the perceived cognitive load.

Considering *untrained workers*, we found that using in-situ instructions for 3 days to learn a task is too long. Therefore, our future work will address finding the optimal duration for using in-situ instructions for learning.

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