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**Decoding the Learning Curve: Improving Operator engagement
with simplified work instructions**

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Abstract

The industry remains highly dependent on human labor and due to high turnover rates, supportive systems are necessary to maintain efficiency and quality. The basis of every process is the work instruction, but in many cases these instructions are overly complicated and contain excessive information, which can overwhelm operators.

The research focuses on observing operators' learning curve, particularly in terms of improvements in time and quality, and how they interpret and engage with the provided work instructions. We aim to track how the time spent focusing on instructions decreases as operators become more proficient. This allows the creation of more abstract and simplified work instructions that highlight only essential information. By emphasizing key elements, operators can work better after the initial training phase.

An experiment was designed, targeted measurements were performed, and the results were analyzed. The learning curves and attentions were recorded during a disassembly process to find the critical elements in the created work instruction and later simplify it.

Keywords: Learning curve, work instructions, operator performance, disassembly task

Chapter 1

Introduction

This study aims to explore the usefulness of the work instructions during repetitive tasks. By examining how instruction abstraction impacts operator performance and learning efficiency, the research seeks to determine if combining steps within instructions can reduce task completion time without sacrificing accuracy. Through detailed time measurements and eye-tracking data, my study investigates the potential to simplify instructions as operators become more familiar with the task, ultimately enhancing productivity and reducing the cognitive load.

1.1 Worker performance

Overall Labour Effectiveness (OLE) is a key performance indicator (KPI) in human-centered manufacturing [1]. It is essential to assess labor efficiency alongside equipment performance. While metrics like Overall Equipment Effectiveness (OEE) and Overall Throughput Effectiveness (OTE) evaluate machine performance, OLE focuses on human factors. OLE and its revised version, ROLE (Revised Overall Labour Effectiveness), measure labor effectiveness by analyzing availability, performance, and quality [2]. Gordon adapted the original OEE formula and introduced OLE as a performance indicator for labor efficiency [3].

Employee availability, including absenteeism, is a major factor in determining whether production benchmarks can be met. Issues like excused and unexcused absences, illnesses, and other factors impacting attendance affect whether the workforce and equipment are fully utilized. Having certified employees scheduled at the correct times in factories with specialized equipment is critical. Indirect factors disrupt production, such as material delays, shift changeovers, idle time, and machine downtime. By analyzing OLE data, manufacturers can develop attendance and absence management policies, optimize scheduling, and ensure that material deliveries align with production needs. This can help mitigate

delays and avoid situations where employees leave their workstations to handle materials, ultimately improving overall efficiency. Performance measures how efficiently a workforce can produce and deliver products. For instance, a lack of trained technicians to set up equipment for the next production run or employees unfamiliar with specific machines can slow operations. Ensuring well-trained employees are available for each task is necessary to maintain optimal performance. Quality in OLE focuses on whether employees follow proper instructions, use the right tools, and adhere to set processes. Supervisors can ensure quality products by maintaining high output standards while reducing rework and waste. This component is essential in preventing errors that can undermine productivity and profitability [4].

The concept of learning curves offers valuable insights into workforce efficiency as operators gain experience with specific tasks. Documented initially by Wright (1936), learning curves illustrate how task repetition leads to reduced time per unit, demonstrating a characteristic pattern in automotive, aerospace, and manufacturing industries [5]. Learning curves are mathematical models that monitor how performance improves with practice, enabling management to predict time and cost reductions as operators become more skilled [6]. Various models, including the log-linear and exponential, track this efficiency gain, offering valuable planning data for production schedules and workforce allocation [7]. Research indicates that task complexity, prior experience, and training significantly impact the learning curve slope, denoting a faster or slower adaptation to tasks [8, 9]. Notably, the effectiveness of a learning curve model in practice depends on ensuring opportunities for operators to engage with varied yet related tasks, which fosters cognitive development and enables the transfer of learned routines [10].

Integrating learning curve data with Overall Labour Effectiveness (OLE) can refine workforce performance evaluations by highlighting areas for skill enhancement and potential efficiency improvements. For example, in mass customization settings, learning curves aid in managing diverse product requirements while minimizing initial losses associated with low proficiency [6].

1.2 Work instruction

Adequate work instructions are essential for enhancing operator performance, especially in environments with high product variability. Well-designed work instructions can reduce errors, improve assembly speed, and decrease cognitive load, contributing to smoother workflows and increased efficiency. Work instructions can be static (e.g., text or images) or dynamic (e.g., animations). Studies indicate [11, 12] that dynamic instructions often yield superior outcomes in terms of efficiency and learning. For example, animated in-

structions can reduce initial assembly times and improve task comprehension by making the process visually intuitive. Watson et al. (2023) found that using animated instructions led to a 37% faster initial build time compared to text-only instructions. High-quality work instructions are essential for ensuring efficient operations and reducing error rates. The critical dimensions affecting instructional quality include clarity, accessibility, and accuracy. Poor quality instructions can lead to delays, higher cognitive load, and even safety issues, particularly in high-risk environments like manufacturing. By focusing on unambiguous, complete, and accessible instructions, organizations can significantly improve the reliability of task execution and operator satisfaction. [13]

However, static instructions, especially those that combine text and images, have shown long-term effectiveness. They tend to require deeper cognitive processing, which may enhance retention and understanding of complex tasks. Effective assembly instructions often use a combination of visual and text cues to build a mental model of the assembly sequence. This approach allows operators to navigate tasks with clarity and precision, making visual work instructions particularly valuable in high-complexity environments [14]. McAlinden et al. (2017) explored the effectiveness of pictogram-based instructions in reducing assembly times and errors. Their study compared pictograms with traditional static images in an aerospace assembly task, finding that pictograms led to a 20% reduction in build times and fewer mistakes. Pictograms are also advantageous because they overcome language barriers, making them effective internationally. This approach aligns with cognitive load theory by minimizing the mental effort needed to understand each step, allowing operators to focus directly on the assembly without the additional burden of interpreting language-specific instructions [15].

As industries transition to a human-centered manufacturing approach, personalized work instructions have gained prominence. Ergonomically optimized work instructions are essential, noting that digital interfaces such as Artificial Reality and Mixed Reality can reduce physical strain and minimize cognitive load by presenting relevant information directly at the workstation [16]. By superimposing instructions on the work area, AR-based instructions eliminate the need for operators to shift their gaze or physically turn to access information, thereby improving task flow and reducing ergonomic risk [17]. Tailoring instructions to individual skill levels and experience is vital, ensuring that operators are neither overwhelmed nor under-challenged. Personalized instructions that adapt to the user's familiarity with the task can enhance learning and engagement, fostering a more effective learning curve [18]. A critical aspect of work instruction design is managing cognitive load. Li et al. (2018) explored various types of information presentation, finding that combining visual aids with concise text reduces cognitive demands on operators. Precise, targeted information supports operators in managing complex tasks by allow-

ing them to focus on the essential steps, which is particularly valuable in multi-variant production environments [19]. The design of effective work instructions involves understanding the task and the user’s needs and cognitive constraints. Integrating findings from cognitive psychology, such as the necessity for a step-by-step hierarchy and visual grouping in instructions, enhances usability and reduces error rates. As industries increasingly adopt digital work instructions, the choice of media—whether static images, text, or animations—should consider both the immediate and long-term goals of task performance and learning [14].

1.3 Eye tracking and information extraction

Eye tracking technology provides valuable information on how people process visual information by capturing gaze patterns, fixation points, and saccadic movements. Eye tracking allows researchers to identify where individuals focus their attention, how long they look at specific elements and the sequence of their gaze across visual stimuli. The methodology relies on detecting corneal reflections using a high-resolution camera, capturing where and for how long users engage with specific areas. This technique has applications in human-computer interaction, marketing, and cognitive psychology, where understanding attention is crucial for optimizing user experiences [20]. Salvucci and Goldberg (2000) emphasize the importance of fixation and saccade identification in eye-tracking data analysis. Fixations are pauses where the gaze remains stable, allowing for detailed information processing, while saccades are rapid movements between fixations. Analyzing these patterns is essential for interpreting cognitive processes, as fixations generally represent points of high attention and information intake. The study also discusses different fixation identification algorithms and their effectiveness, indicating that careful selection is necessary to maintain data accuracy and reduce noise in eye tracking analysis [21].

Advances in wearable eye-tracking technology, such as head-mounted devices, have broadened the scope of eye-tracking by enabling real-world, dynamic studies. Cognolato et al. (2018) review modern head-mounted eye-tracking devices, highlighting their application in diverse environments, from assistive technology for individuals with disabilities to rehabilitation and daily living support. These devices capture not only gaze direction but also pupil size and head orientation, enabling comprehensive monitoring of visual attention in complex, real-life settings. The flexibility of these trackers has made them valuable tools [22]. Eye-tracking technology is widespread across fields, including usability research. Using advanced metrics such as heat maps and scan paths, eye tracking can illustrate visual attention distribution and patterns of interest across a screen or physical space. These metrics are especially useful in user experience research, where identify-

ing areas that are frequently viewed helps refine design elements for enhanced usability. The article also highlights the increasing popularity of remote and wearable eye tracking devices, which can be adapted to controlled environments and natural settings [23].

Alton et al. (2014) examined how eye-tracking data can inform the design of form instructions, especially to optimize visibility and placement for better user engagement. Their study found that the visibility of instruction significantly impacts user interaction, with instructions placed above the form fields garnering the most attention and engagement, particularly for users with lower literacy. Hidden instructions, such as those behind buttons or text links, were less effective and often overlooked by users. Their research underscores the importance of instruction visibility and proximity to input fields, suggesting that placing critical information in a user's direct line of sight can improve form completion rates and reduce errors [24].

Chapter 2

Current study and research hypothesis

This study explores the effectiveness and usefulness of work instructions in a controlled disassembly task, focusing on how instruction format impacts task performance and learning efficiency. The primary objective is to assess whether the combination of steps in the instruction sequence can reduce the task completion time. Initially, detailed instructions may aid participants in understanding each action thoroughly, but as participants become more familiar with the task, fewer, more consolidated instructions might streamline the process. Furthermore, I hypothesize that participants will require fewer instructions to perform the task accurately over time. A learning curve is expected as participants repeat the disassembly task, allowing them to better understand the task sequence and to depend less on explicit guidance. Particular instructions, remarkably straightforward actions like where to place removed components, may be memorized quickly. Because these steps are simpler and repetitive, they likely impose a low cognitive load, allowing participants to remember them more easily. The experiment includes 12 measurements for each participant, evenly divided between two instruction formats. In the first six trials, participants use a detailed, step-by-step instruction sequence, helping them become familiar with each part of the disassembly task. The instructions are more condensed in the following six cycles, combining related actions into a single image. For example, one image might show the removal of the part and its designated placement location. This setup allows for observing changes in task efficiency and participant reliance on the instructions over time. The findings of this study could improve the understanding of instructional design for repetitive technical tasks, particularly in industrial settings. Insights may inform how instructions can be optimized to support both learning and efficiency, balancing thorough guidance for beginners with minimal instructions for experienced operators.

Chapter 3

Description of the experiment

The experiment involved disassembling a battery control unit as seen in Figure 3.1. The goal was to see the role and significance of the work instructions. During the process, participants had to unscrew different parts, remove cables and components, and place these elements and the corresponding nuts in designated boxes. The participants encountered the task for the first time during the experiment, so nothing influenced their performance in the task presented. The order of the subtasks was predetermined and clearly outlined in the work instructions. Two different screwdriver heads, necessary to complete the task, were provided and readily available to the participants. The work instructions were displayed on a monitor placed in front of them, allowing them to navigate forward and backward if they made any errors during the process. Throughout the experiment, participants wore eye tracking glasses to monitor the parts of the instructions they focused on the most frequently. The total time to complete the task and the time spent on each instruction image were also measured. The quality was checked by me during, and after each experiment and noted down.

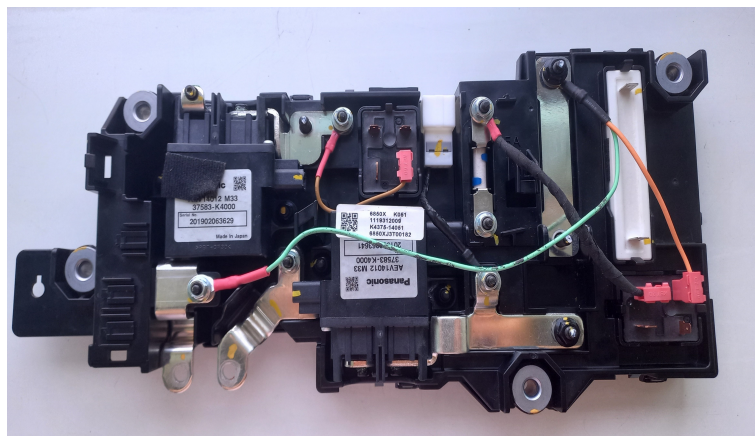


Figure 3.1: The part that needed to be disassembled

3.1 Participants

Four individuals participated in the experiment, all male. The group included two BSc students, one PhD student, and one university employee. Of these four, two participants had previous experience with the use of screwdrivers and performing similar technical tasks, which could influence their familiarity with the disassembly process. The selection of the participants was based on the acquaintance of the investigators, which ensured a comfortable and cooperative environment for the experiment. All participants provided their informed consent prior to participating in the study.

3.2 Instructional design

The work instructions for the disassembly task were presented as images on a monitor, showing the participants what they needed to do. Four types of instructional images were used:

1. **Screwdriver Head Change:** These images indicated when the participants needed to change the screwdriver head to fit the task (Figure 3.2a).
2. **Part Placement:** The second type of instruction showed where the removed components should be placed out of the three storage containers (Figure 3.2b).
3. **Nut Removal:** The third type of instruction showed which nut in the battery control unit needed to be unscrewed (Figure 3.2c).
4. **Part Removal:** The fourth type of image indicated which part should be removed during the disassembly process (Figure 3.2d).

Each task within the instruction sequence was numbered to guide participants through the disassembly process step-by-step. Critical elements in each instructional image were highlighted to ensure clarity. Specifically, the part participants needed to work on was marked with a red rectangle. Additional visual cues included a red screw icon, as seen in Figure 3.2c, signaling when a nut needed to be unscrewed, and a red arrow, as seen in Figure 3.2d, indicating which part should be pulled off or removed. These markers were designed to make the instructions intuitive and reduce potential errors in following the sequence of tasks.

In addition, two different types of work instructions were presented to the participants, one detailed and one merged. In the first arrangement, each step was displayed in a separate image. The instructions were switched to a second sequence after participants became more used to the disassembly task. In this sequence, both the action of removing

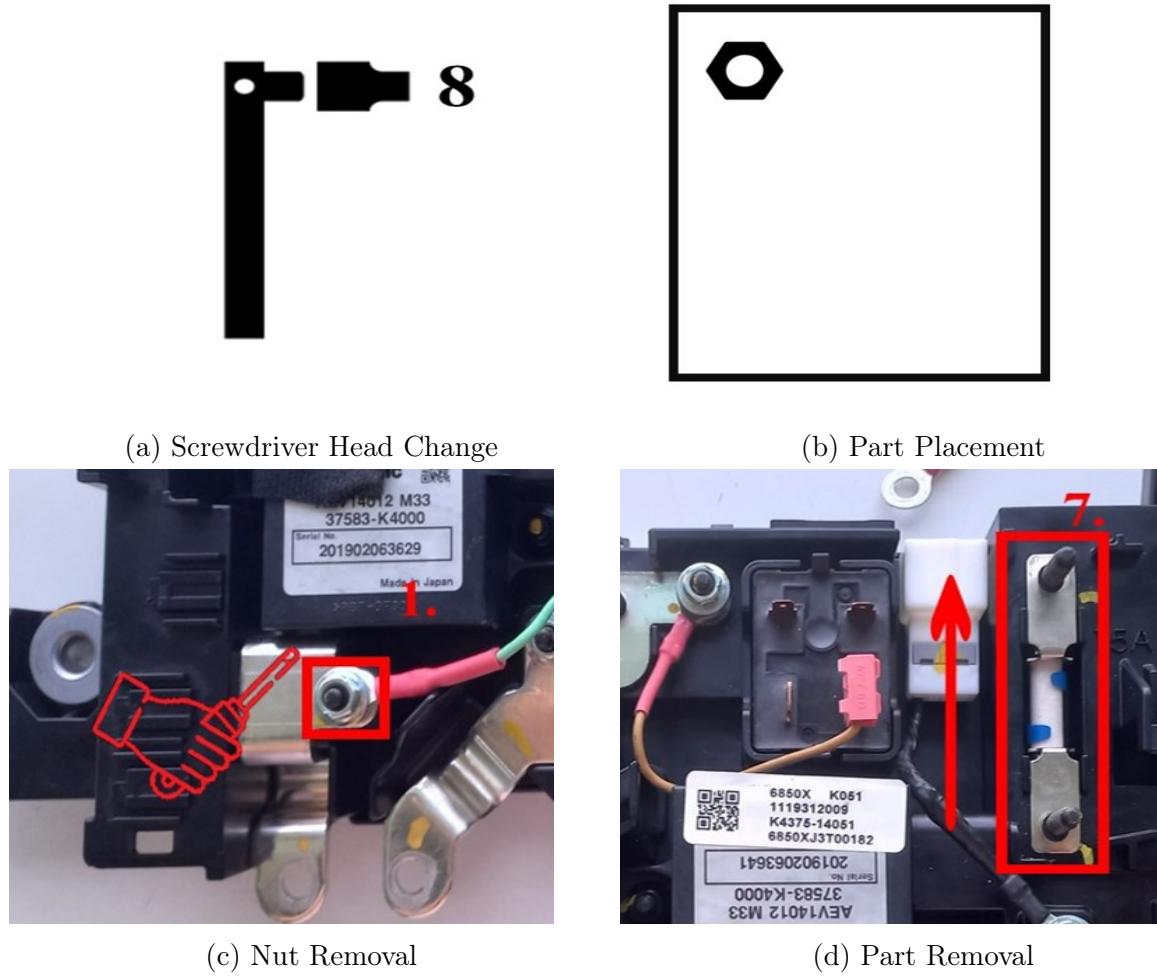


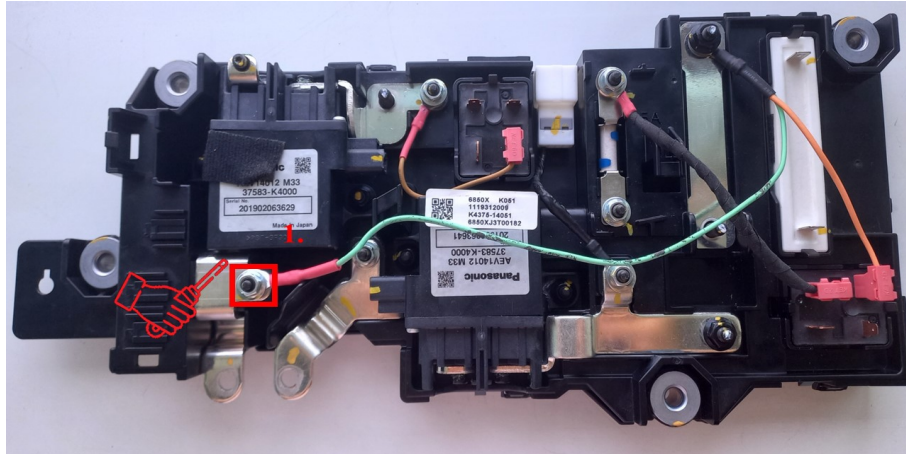
Figure 3.2: The four different instruction types

a part and the storage location where it should be placed were combined into a single image.

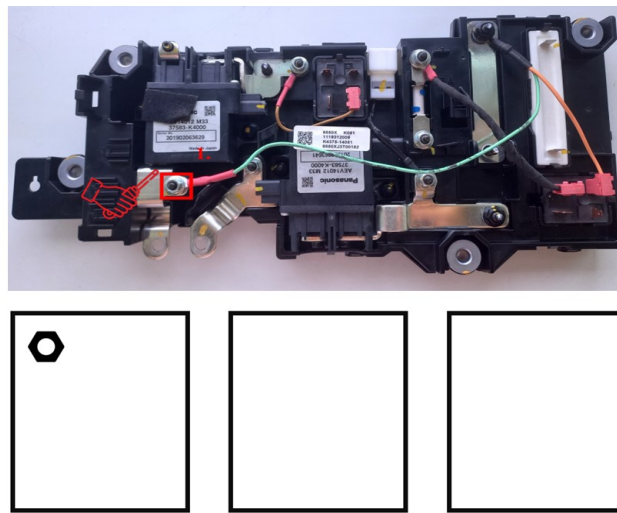
3.3 Experiment design and procedure

The experiment was carried out in the Industry 5.0 laboratory of the University of Pannonia. Each session was designed to last approximately one hour, which allowed each participant to complete the task comfortably. A laptop was placed in front of them in a comfortable position to press the buttons to switch between tasks.

Before the experiment, the participants were introduced to the task and tools to ensure they were familiar with the procedure and equipment. They were shown the battery control unit they would disassemble, instructed on how to change the screwdriver heads, and introduced to each type of instruction image, clarifying what actions each visual cue represented. In addition to task details, participants were introduced to the eye-tracking



(a) An instruction from the first part of the experiment



(b) An instruction from the second part of the experiment

Figure 3.3: Example instructions from the experiment

glasses used to monitor their attention to instructions. After putting on the glasses, they underwent a calibration process that involved focusing on a black pattern displayed on a white card. This step ensured the accuracy of the eye-tracking data by aligning the glasses with each participant's gaze. Once calibration was completed, recording began to capture the participants' relations with the instructions shown on the computer rather than the disassembly actions themselves. This recording was continuously ran throughout the experiment to track which parts of each instruction captured the participants' focus.

The disassembly task was initiated by displaying a "start" image on the laptop screen, which allowed participants to begin by clicking to proceed to the first instruction. There were no distractions during the experiment, ensuring a focused environment and that all sessions proceeded smoothly. I was present throughout each experiment to observe the process and note any mistakes made by the participants. Furthermore, potential errors

could be reviewed later through the eye-tracking recordings, providing a comprehensive data set for post-experiment analysis. The "instruction-showing" program was developed in Python and displayed step-by-step instructions on the laptop. The start and end times were recorded for each step, creating precise time data for each action. This setup resulted in 12 individual Excel files per participant, each containing detailed time data and a video recording of the eye-tracking data, allowing further analysis of task performance and instructional interaction.

3.4 Data processing

The data collected in this study comprises three main areas: eye tracking data, work instruction data, and worker performance assessment. These data sets allow for a comprehensive analysis of task efficiency, instructional interaction, and individual learning progress.

Eye tracking data was captured using Tobii Pro Glasses 2, with analysis performed through the Tobii Pro Lab software. This tool enables detailed analysis by allowing specific instruction images to overlay the eye-tracking video recordings. Tobii Pro Lab identifies visual attention patterns by highlighting focus areas and counting the frequency and duration of gaze points on each instruction image. This analysis is crucial to understanding the instruction elements that participants attended most frequently, providing insight into potential areas where instructions can be minimized or eliminated as participants become more familiar with the task.

The work instruction data includes the time metrics recorded during each step of the disassembly task. These measurements capture the start and end times for each instruction, allowing the calculation of the total time spent on each step. Metrics such as average times, standard deviations, and learning curve trends are derived from these data, offering insights into how participants' efficiency improved over the trials. Learning curves, in particular, reveal the reduction in time as participants advance through repeated task sequences, indicating familiarity and increasing proficiency.

Performance assessment in this study is based on time data and observed errors during the experiment. Completion times serve as a primary performance metric, with time improvements reflecting the impact of familiarity and instructional design on task efficiency. In addition, errors observed during the experiment provide a qualitative aspect to the performance evaluation. By examining both time efficiency and accuracy, I can gain insights into participants' skill acquisition and the instructional elements that either facilitated or hindered their success.

Chapter 4

Exploratory results

This chapter presents an initial analysis of the data collected during the experiment, focusing on the patterns observed in task performance and instruction efficiency. By examining learning curves and time metrics, I can understand how participants adapted to the disassembly task over repeated trials. These exploratory results provide a foundation for understanding the impact of instruction design and highlight potential areas for refinement in future tasks.

4.1 Learning curves

The data collected from each participant across the first and last six trials provides insights into learning trends throughout the experiment. The time taken for each disassembly reveals how task familiarity impacts efficiency and highlights the learning curve for repetitive disassembly tasks. Initial trials indicate that participants spent more time completing each step, likely due to unfamiliarity with the task sequence and the instruction format. For example, average completion times were higher in the first six trials, reflecting the need for more careful attention to instructions. As participants progressed through the trials, the time per task decreased significantly. This suggests a reduction in cognitive load as participants internalized more straightforward actions, allowing for faster performance with fewer instructions. Comparing the first and last sets of trials shows an overall improvement in time efficiency. The decrease in average time across the trials can be visualized as a learning curve, with sharp drops at earlier stages and flattening as participants reach optimal performance, as seen in Figure 4.1.

Before the experiments, it was established that there would be two sets of six trials each, allowing for a clear comparison of results among different participants. The learning curves indicate that not all participants fully stabilized their performance times within the first six trials. However, Participant 3's times did stabilize within this initial set as

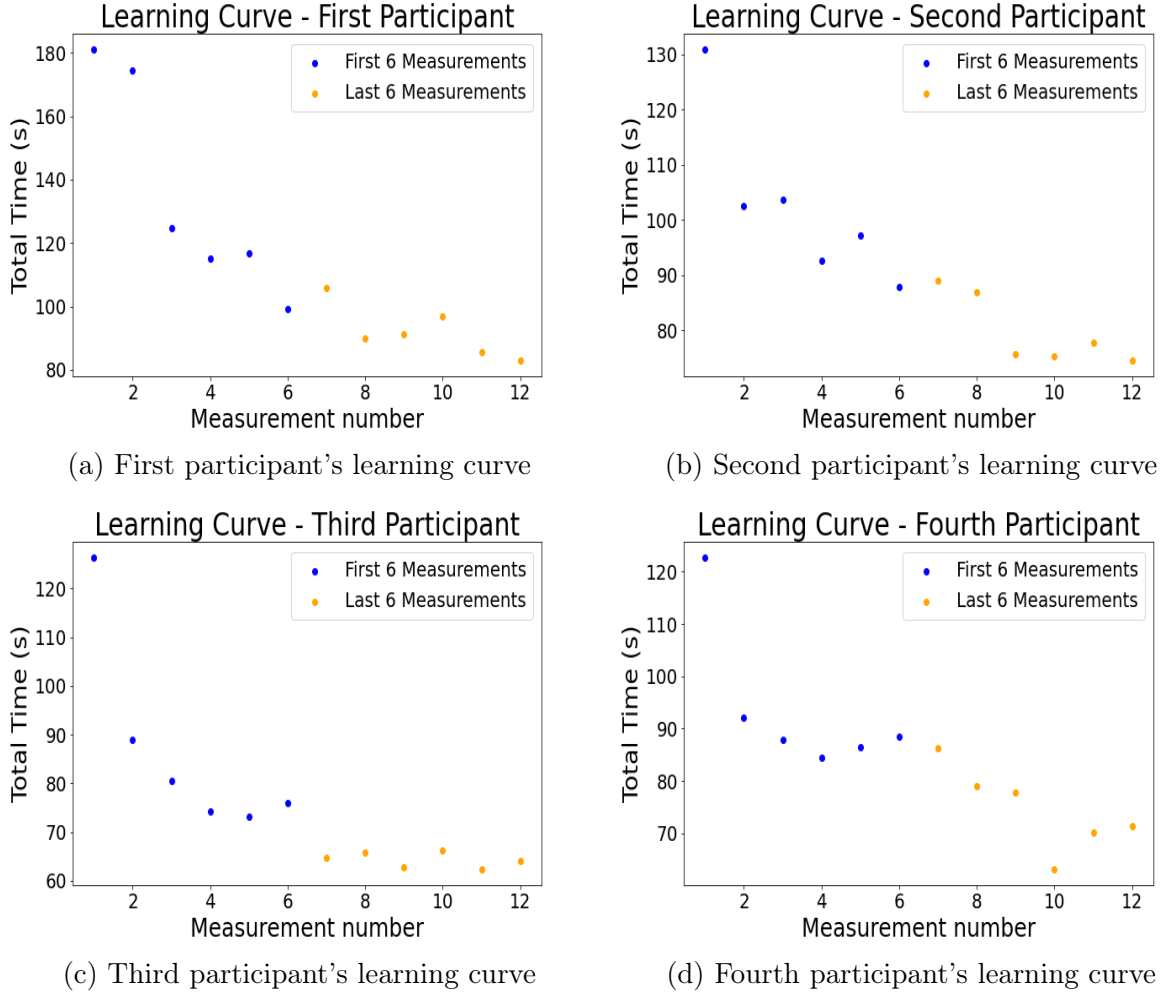


Figure 4.1: The four participants' learning curves

seen in Figure 4.1c, displaying a clear distinction in completion times between the two instruction formats. This participant's data exemplifies the impact of instruction changes on efficiency, providing a notable benchmark for the effects of instruction consolidation.

The average completion times (t_{mean}) across participants show a clear improvement from the first set of six trials to the second, illustrating the impact of task familiarity and consolidated instructions. As shown in Table 4.1, Participant 1's average time decreased from 135 seconds in the first six trials to 92 seconds in the final six, reflecting a significant gain in efficiency. Standard deviations (t_{std}) generally decreased across trials, indicating

Part.	First 6 t_{mean} (s)	Last 6 t_{mean} (s)	First 6 t_{std} (s)	Last 6 t_{std} (s)
P1	135	92	34	8,3
P2	102	80	15	6,4
P3	87	64	20	1,6
P4	94	75	14	8,1

Table 4.1: Means and standard deviations

improved consistency as participants became more comfortable with the task. In particular, Participant 3 demonstrated the most stable performance, with a standard deviation of only 1.6 seconds in the last tests, suggesting a high level of proficiency and minimal variability at the end of the experiment. This overall reduction in time and variability underscores the learning effect, with instruction modifications contributing to both speed and reliability in task execution.

4.2 Analysis of performance improvement with merged instructions

The hypothesis for this section was that merging instructions would decrease the overall task completion time, as participants could perform multiple related actions in a single step, minimizing pauses for instruction changes.

Table 4.2 shows the original set of tasks compared to the modified task list where specific steps were merged. In the original sequence, tasks such as “screwing” and “placing”

Original		Merged	
Number	Task	Number	Task
1.	head change	1.	head change
2.	screwing	2.	screwing and placing
3.	placing	3.	head change
4.	head change	4.	screwing and placing
5.	screwing	5.	removing and placing
6.	placing	6.	head change
7.	removing	7.	screwing and placing
8.	placing	8.	removing and placing
9.	head change	9.	screwing and placing
10.	screwing	10.	removing and placing
11.	placing	11.	removing and placing
12.	removing	12.	screwing and placing
13.	placing	13.	removing and placing
14.	screwing		
15.	placing		
16.	removing		
17.	placing		
18.	removing		
19.	placing		
20.	screwing		
21.	placing		
22.	removing		
23.	placing		

Table 4.2: The tasks during the experiment

Task type	Number of occurrences	Average time
head change	3	3-6 s
placing	10	1-2 s
removing	5	2-6 s
screwing	5	7-15 s

Table 4.3: Average time for each task

were presented as separate actions, resulting in a total of 23 steps. In Table 4.3, it can be seen how much time each task took on average. In the merged version, these related actions were combined when feasible, reducing the instruction count to 13 tasks. For example, separate tasks for “screwing” and “placing” have been combined into “screwing and placing,” thereby simplifying the instructions and potentially reducing the cognitive load for participants.

Table 4.4 shows the relationship between the combined tasks and their original components. Each row in this table represents a consolidated task alongside the original set of steps it encompasses. This format streamlines the workflow and allows us to observe how combining instructions affects task efficiency and participant performance. By comparing results from the merged and separated instruction sets, we can assess the impact of instructional design on task completion times.

In addition to examining the learning curves, the average time and standard deviation of each individual task can be compared, as shown in Figure 4.2. This comparison highlights that certain tasks required very little time, often accompanied by low variability, suggesting that these actions became routine and required minimal cognitive effort. The tasks shown in the same color on the figure indicate those merged in the merged

Merged	Seperated
1.	1.
2.	2. - 3.
3.	4.
4.	5. - 6.
5.	7. - 8.
6.	9.
7.	10. - 11.
8.	12. - 13.
9.	14. - 15.
10.	16. - 17.
11.	18. - 19.
12.	20. - 21.
13.	22. - 23.

Table 4.4: The task numbers that were merged

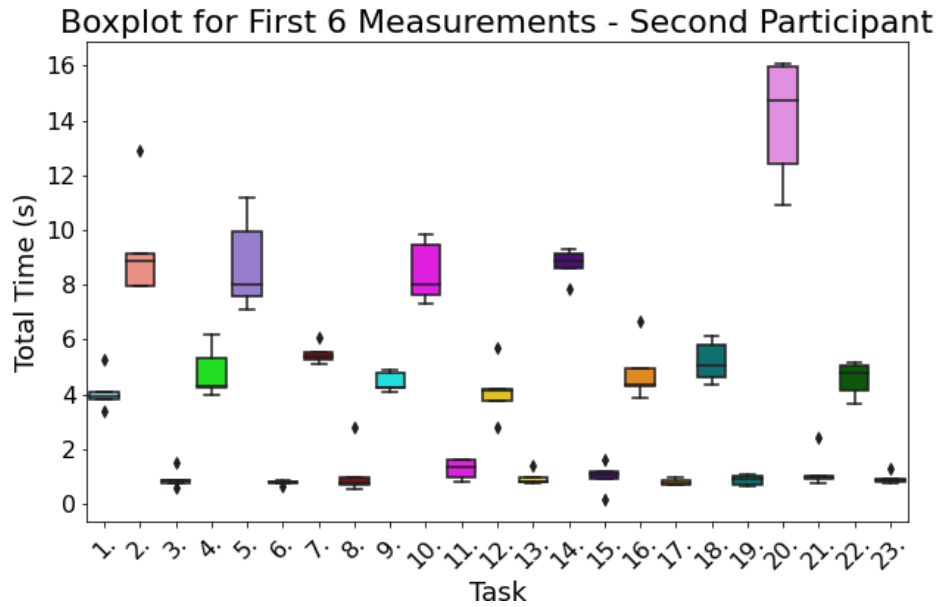


Figure 4.2: The first six measurements' task times for the Second Participant

instruction set, providing a visual overview of how combining similar tasks impacted time consistency and efficiency. This view helps to pinpoint tasks that could be simplified, as participants quickly internalize them with minimal need for extended instructions.

By summing the times for tasks combined in the merged instruction set, we can create a bar chart to compare the total mean time spent on each task before and after merging the instructions, as seen in Figure 4.3. This visualization allows us to assess whether time decreased or increased for each united task. The bar chart effectively highlights any reductions in time, indicating where the merged instructions streamlined the process or revealed if certain tasks required more time in their new format.

The bar charts reveal instances where the average time spent on a task was higher during the second set of six measurements. Notably, three of these cases involved tasks that were not merged, as seen in Figure 4.3a and Figure 4.3d, specifically the screwdriver head change. This suggests that while participants became more efficient in certain areas, some non-merged tasks still required more time, potentially due to the physical nature of the action or increased cognitive load. Furthermore, there were two instances where the average time increased for a merged task in the second set of measurements, as seen in Figure 4.3d, the 16. - 17. and 20. - 21. task. These exceptions provide insight into which tasks may benefit from further refinement or adjustment in the instructional design, mainly where merged instructions were not as effective in reducing task time as anticipated.

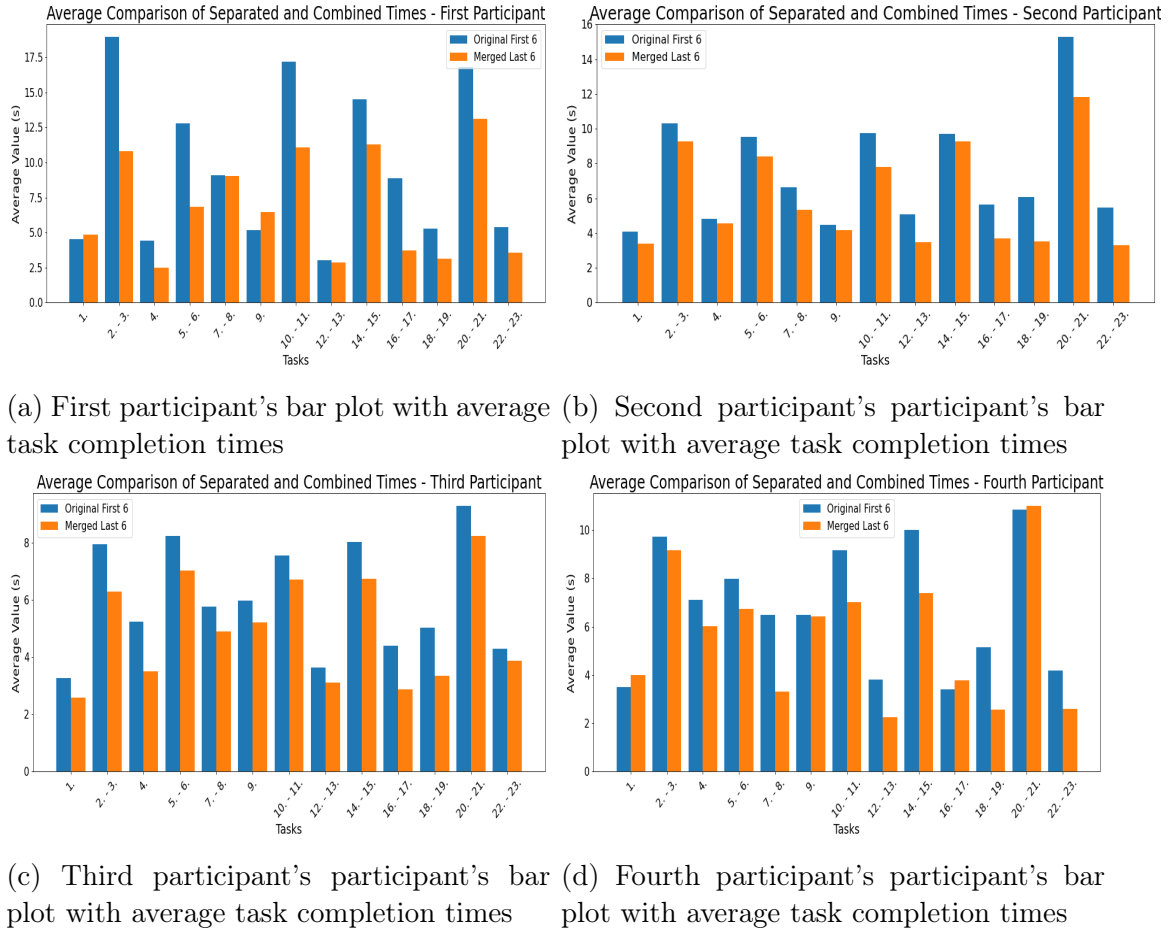


Figure 4.3: The four participants' participant's bar plot with average task completion times

To compare the time differences quantitatively, we can divide the values from the last six measurements by those from the first six. This calculation provides a ratio that indicates the change in time for each task, with values below 1.0 showing a decrease in time and above 1.0 indicating an increase. This ratio allows for a clear numerical comparison of time efficiency, which is beneficial for identifying tasks where merged instructions resulted in significant time savings or, conversely, where time increased.

Table 4.5 presents the mean time ratios for each task. Notable improvements can be seen in Task 16. -17. , where Participant 1's ratio is 0.421, and Task 18. - 19. , where Participant 4's ratio is 0.497. These low ratios highlight significant time reductions, likely due to participants' familiarity with the task sequence. However, some tasks show an increase in time, as previously mentioned.

This analysis provides a clear view of performance, highlighting time savings and areas that require further adjustments for optimal task completion.

Task	P1 Ratio	P2 Ratio	P3 Ratio	P4 Ratio
1.	1,073	0,834	0,791	1,137
2. - 3.	0,571	0,900	0,792	0,941
4.	0,566	0,946	0,667	0,848
5. - 6.	0,535	0,883	0,852	0,844
7. - 8.	0,990	0,801	0,849	0,509
9.	1,253	0,938	0,871	0,994
10. - 11.	0,643	0,799	0,886	0,766
12. - 13.	0,941	0,690	0,855	0,589
14. - 15.	0,775	0,952	0,839	0,739
16. - 17.	0,421	0,654	0,650	1,113
18. - 19.	0,598	0,582	0,667	0,497
20. - 21.	0,780	0,773	0,888	1,013
22. - 23.	0,667	0,601	0,903	0,621

Table 4.5: Mean time ratios

4.3 Eye tracking

The eye-tracking data collected during the experiment provides insight into participants' focus on various instruction elements and the efficiency of task navigation. By analyzing gaze patterns, we can determine which parts of the instructions attracted the most attention and how this changed over time. This information is critical for understanding whether participants relied less on instructions as they became familiar with the tasks, indicating the potential for instruction simplification in repetitive processes. Additionally, the data helps identify which elements of the instructions were particularly engaging or confusing, guiding future improvements in instructional design.

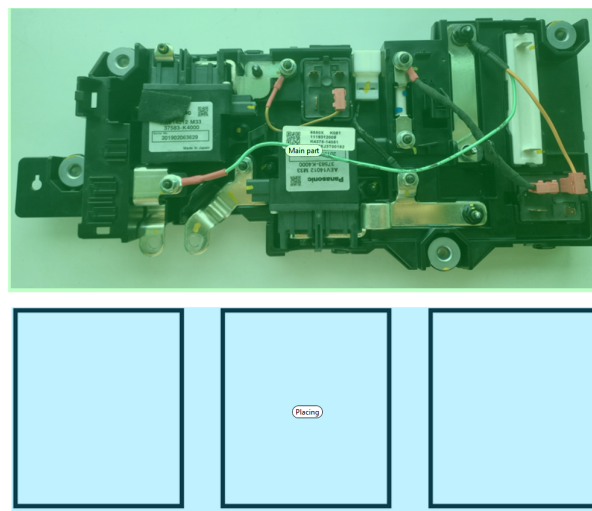


Figure 4.4: Areas of interest

In this study, Tobii Pro Glasses 2 were used to capture precise eye tracking data, allowing detailed insights into where participants focused their attention during the disassembly task. This lightweight and wearable eye tracker is designed for natural viewing and interaction, making it ideal for real-world applications such as this experiment [25]. The data from the glasses were analyzed using the Tobii Pro Lab software, which allows advanced visualization and analysis of gaze patterns, and comes with features such as image overlays and heat maps [26].

In the last six measurements, examining where participants directed their attention with the merged instructions is useful. This analysis helps identify which parts of the instructions are essential and which might be unnecessary. With the Tobii Pro Lab software, I could track precisely when the participants looked at each instructional image and measure the duration of their gaze. The software allowed me to define specific areas of interest (AOIs) within each image, as seen in Figure 4.4. It made it possible to analyze which parts of the instructions captured attention and for how long. This data could then be exported, providing detailed metrics on participants' time focusing on each AOI.

Table 4.6 displays the time that participants spent focusing on specific areas of interest (AOI) within each merged instruction image, particularly for the central part of the task and the placing action. For each task, the duration in seconds reflects how long participants focused their attention on these critical areas.

The data show that the main part of the task consistently required more visual attention than the placing action, as can be seen on the heat maps in Figure 4.5. For example, in Task 6, participants spent an average of 5.24 seconds looking at the main part compared to only 0.94 seconds for placing. This pattern suggests that participants needed more time to comprehend and act on the main disassembly steps, while the placing actions required minimal focus, likely due to familiarity and simplicity. Such insights help identify which instructional elements can potentially be minimized or removed in future iterations to streamline the process, for example, in my case, the placement could be removed after some time.

Measurement number	Main part looking time (s)	Placing looking time (s)
10.	4,56	0,66
11.	4,40	1,26
12.	5,24	0,94

Table 4.6: Times spent on each AOI by Participant 3

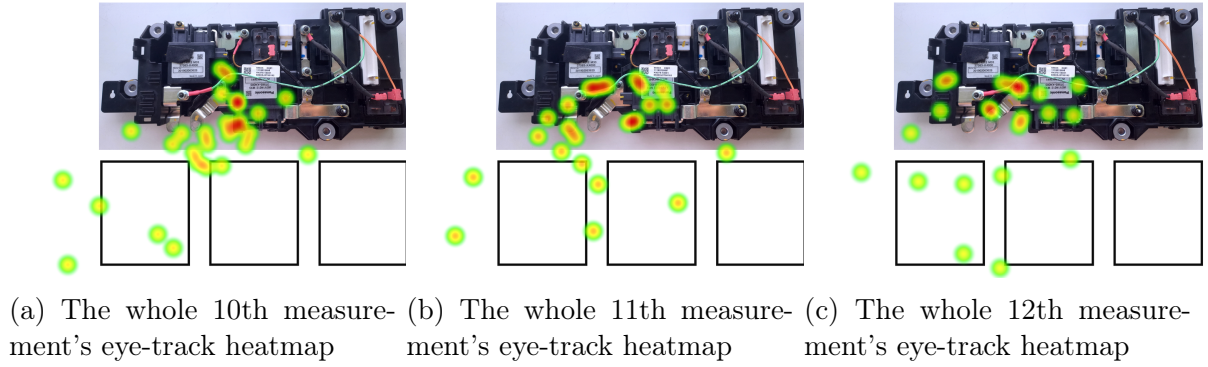


Figure 4.5: Example heatmaps of the eye movements of Participant 3

4.4 Discussion and findings

The results of the experiment indicate that the merging of particular instructions improved the overall performance of the task, as participants completed tasks more efficiently with fewer consolidated steps. With the merged instructions, there was less time distribution, and the work became more predictable. This supports the idea that fewer instructions can simplify task execution once participants know the actions. In addition, the experimental setup effectively demonstrated a structured design of experiments, allowing for controlled comparisons across different instruction formats and supporting the analysis of task-specific learning curves. This setup has also made it possible to account for and eventually measure forgetting factors, which may impact performance over time and with repeated tasks.

Based on eye-tracking data, there are further opportunities for refining work instructions to eliminate redundant information. Specifically, the locations for placing components could be shown only initially, indicating which box is intended for each type of item, and then omitted in later instructions. Furthermore, the data suggest that instructions for changing the screwdriver head could be phased out as participants become familiar, focusing only on essential task steps as needed. These findings offer insights for future work instruction designs, emphasizing the potential to simplify guidance as task familiarity increases.

Chapter 5

Conclusions and further steps

This study explored the impact of instruction design on task performance within a controlled disassembly experiment, focusing on the effects of merging particular instructions and using eye tracking data to assess participant attention. The findings suggest that the merging of instructions, particularly for familiar actions, effectively improves task efficiency by reducing the cognitive load on participants. The merged instruction set proved beneficial, allowing participants to complete tasks more quickly without sacrificing accuracy, as repetitive actions were grouped, simplifying the overall process. The experimental design used in this study effectively generated clear comparisons and valuable insights. It provided a foundation for analyzing the learning curves associated with repetitive disassembly tasks. It highlighted how participants adapted to the task over time and what elements became redundant as the familiarity grew. The design also set the stage for future studies to incorporate and measure the forgetting factor, which can affect long-term task retention and consistency of performance.

Eye tracking data was crucial in showing areas where instructions could be further abstracted. The analysis revealed that the instructions for the placement of the components could be minimized after the initial steps, as participants quickly learned which items belong to each box. Similarly, instructions for changing screwdriver heads could be phased out over time as participants became more accustomed to these actions. These insights indicate a clear path to refine work instructions by focusing only on the necessary guidance and avoiding redundant details in repetitive tasks.

Further studies could implement adaptive instruction systems that dynamically adjust based on participant proficiency and error rates, offering a more personalized approach to work instructions. Additionally, this research establishes a foundation for hesitation detection, allowing future instruction systems to offer specific guidance whenever a worker hesitates, addressing moments of uncertainty to facilitate smoother task execution.

In conclusion, this study highlights the potential to improve instructional design in

industrial and technical training settings. Using eye-tracking data and analyzing trends in task performance, we can develop more efficient, user-centered instructional models that enhance learning, minimize errors, and adapt to meet participants' needs over time.

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