The impact of work instruction simplification on operator performance and learning curve efficiency

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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. This 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 and abstractions of it. 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 were recorded during a disassembly process to find the critical elements in the created work instruction and later simplify it. The results indicate that simplified instructions, introduced after an initial learning phase, led to shorter task completion times without increasing error rates. These findings suggest that instruction abstraction can support operator efficiency during repetitive tasks. Future research will explore adaptive instruction systems and their integration in industrial environments with larger and more diverse participant groups.

Keywords: Work instruction · Human-centered · Learning-curve · Abstraction

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 our study investigates the potential to simplify instructions as operators become more familiar with the task, ultimately enhancing productivity and reducing the cognitive load.

In modern industrial environments, high operator turnover and product variability demand flexible and effective training methods to maintain productivity and minimize errors [5, 8]. As new workers are often introduced to complex manual tasks, the design of work instructions becomes critical for task efficiency and accuracy. Yet, overly detailed instructions can overwhelm novices, while abstract ones may fail to provide sufficient early guidance [11, 13]. From a cognitive ergonomics perspective, effective instructions must manage cognitive load by minimizing extraneous mental effort [1, 11]. Prior studies emphasize that visual clarity, step segmentation, and multimodal presentation significantly influence learning and task performance [9, 17, 15].

This study is an exploratory investigation into how instruction simplification, specifically merging low-complexity steps into fewer visual cues, affects operator performance in a repetitive disassembly task. Following an initial familiarization phase, we hypothesize that simplified instructions can reduce task time without increasing error rates. The paper is structured as follows: Section 2 reviews related literature; Section 3 presents the experimental setup; Section 4 discusses the results; and Section 5 concludes with implications, limitations, and future directions.

2 Related works

2.1 Worker performance

Overall Labour Effectiveness (OLE) is a key performance indicator (KPI) in human-centered manufacturing [12]. 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 [5]. Gordon (2008) adapted the original OEE formula and introduced OLE as a performance indicator for labor efficiency [8].

Employee availability, including absenteeism and shift planning, significantly impacts whether production targets are met. Attendance issues and scheduling mismatches reduce workforce and equipment utilization. Indirect disruptions affect efficiency, such as material delays, idle time, or shift transitions. OLE data can support better scheduling, absence management, and material flow alignment, helping avoid delays and unnecessary operator movement. Performance reflects how efficiently the workforce delivers output. A lack of trained staff or unfamiliarity with equipment can hinder operations, highlighting the need for proper task-specific training [8]. 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 [8].

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 [22]. 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 [2]. 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 [3, 4]. 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 [21]. Integrating learning curve data with 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 [2].

The OLE framework is a useful tool for interpreting human performance, though it has limitations. Its reliance on time-based and observational data can introduce subjectivity, especially in small-scale studies. Continuous monitoring may also raise privacy concerns [5, 8].

2.2 Work instruction

Adequate work instructions are essential for enhancing operator performance, especially in environments with high product variability [13]. 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 [20, 19] that dynamic instructions often yield superior outcomes in terms of efficiency and learning. For example, animated instructions 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. [9]

However, static instructions, especially those that combine text and images can also be effective [18]. 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 [1]. 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 [13].

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 Augmented Reality (AR) and Mixed Reality (MR) can reduce physical strain and minimize cognitive load by presenting relevant information directly at the workstation [6]. 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 [15]. 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 [17]. 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 allowing them to focus on the essential steps, which is particularly valuable in multi-variant production environments [11]. 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 [1].

Instructional design should consider individual differences in working memory and reasoning, as these influence how users handle abstraction [16]. Varying abstraction levels affect user performance and satisfaction, especially when matched to expertise [10]. Supporting cognitive processes like pattern recognition and structure identification can enhance instructional abstraction [14]. While prior studies explored how instruction format affects cognitive load and task performance [1, 11, 13], few have investigated how abstraction over time impacts learning and efficiency. Most research emphasizes initial performance, not long-term learning curves or instruction transitions. This study contributes by examining how instruction simplification interacts with operator learning in an industrial context.

3 Design of experiment

The experiment involved disassembling a battery control unit as seen in Figure 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 disassembly task was selected for its relevance to industrial settings and its suitability for controlled experimentation. Its structured, low-complexity steps allow for clear instruction, observation, and analysis. Visual instructions were used due to their clarity, ease of interpretation, and ability to reduce cognitive load by emphasizing key actions and components that are crucial in tasks requiring speed and precision.

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. The total time to complete the task and the time spent on each instruction image were measured. The quality was checked during the experiment and noted down in each round. To ensure measurement consistency, a predefined checklist of expected task steps and common errors was used throughout all sessions. The same researcher observed each session and recorded it using Tobii eye-tracking glasses. This enabled post-experiment verification of time logs and error detection.

3.1 Participants

Eight individuals participated in the experiment, seven female and one male. The group included seven BSc students and one PhD student. Three participants had prior experience with using screwdrivers and performing similar technical tasks, which could influence their familiarity with the disassembly process. Participants were chosen through a call for volunteers distributed within the university, and they joined the study voluntarily. This open recruitment ensured a diverse but motivated participant pool. All participants provided their informed consent before participating in the study. While the participants were selected based on availability, the small sample size (n = 8) and gender imbalance (7 female, 1 male) may limit the generalizability of our findings.

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 as seen in Figure 2:

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

Additionally, two different types of work instructions were presented to the participants as seen in Figure 3: one semi-detailed and one short. In the first arrangement, both the action of removing a part and the storage location where it should be placed were combined into a single image, but the main steps were displayed in a separate image. In the short version, multiple steps were performed on the same image, and the place of storage was indicated only once for each variety. The instructions were grouped based on the the cables. Each cable had at least one nut, which had to be screwed off, and one connector, which had to be removed.

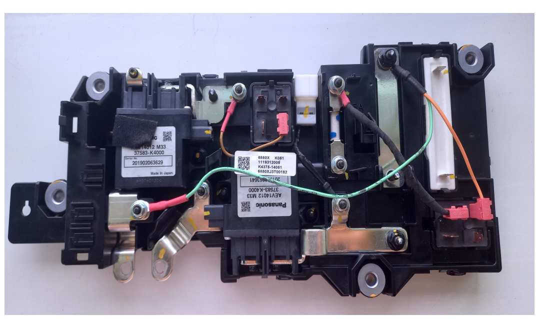


Fig. 1: The part that needed to be disassembled

3.3 Data processing

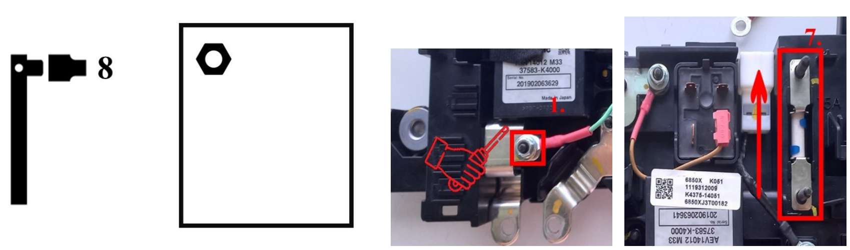
The data collected in this study comprises two main areas: work instruction data and worker performance assessment. These data enable a comprehensive analysis of task efficiency, instructional interaction, and individual learning progress.

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. All sessions were monitored by the same facilitator, who manually noted any observable task errors based on a predefined checklist of expected actions (e.g., missed screw, incorrect part placement). By examining both time efficiency and accuracy, we can gain insights into participants' skill acquisition and the instructional elements that either facilitated or hindered their success.

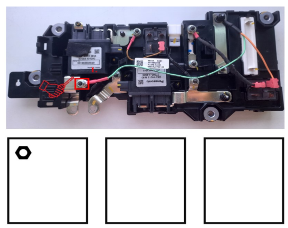
4 Exploratory results

This section 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, we 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.

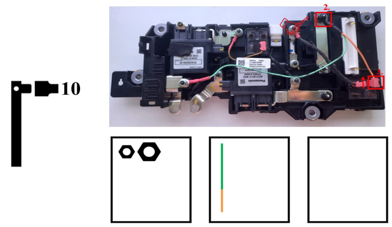


(a) Head Change (b) Placement (c) Nut Removal (d) Part Removal

Fig. 2: The four types of visual instructions used in the study.



(a) A semi-detailed instruction



(b) The shortened version of the instructions

Fig. 3: Example instructions from the experiment

Participants were divided into two groups to assess the impact of initial instruction type on long-term performance. Group A (participants 1, 3, 5, 6) started with the shortest version of the instructions, while Group B (participants 2, 4, 7, 8) began with the slightly longer, semi-detailed variant. Two weeks later, all participants repeated the disassembly task using only the shortest version.

4.1 Experiment protocol 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. Eight people participated in the experiment, and they were divided into two groups. The experiment was repeated with the same participants two weeks later to study the effect of the forgetting factor. One of the groups used the short instruction set in both sessions, while the other group began with a more detailed instruction set in the first session and used the short instruction set in the second session.

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.

A laptop was placed in front of them in a comfortable position to press the buttons to switch between tasks. 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. We were present throughout each experiment to observe the process and note any mistakes made by the participants.

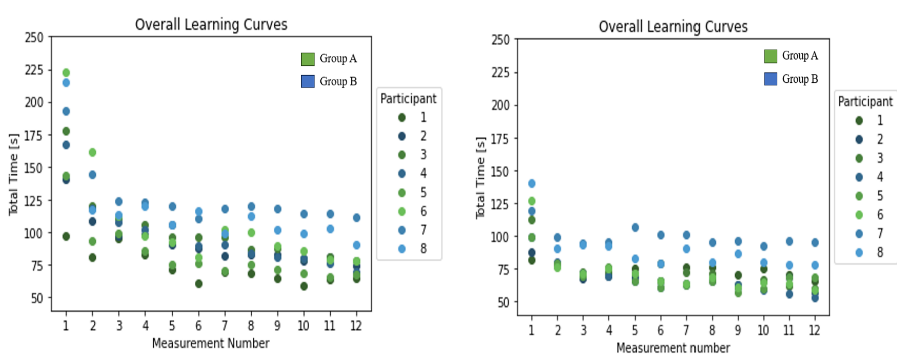
The "instruction-showing" program was developed in Python environment and displayed step-by-step instructions on the laptop. The start and end times were recorded for each step, creating precise time data for each action. This setup resulted in 12 individual Excel files per participant, each containing detailed time data.

4.2 Learning curves

The data collected from each participant across the two sessions 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 rounds, 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.

In Figure 4, all participants' completion times can be seen. It can be seen that after four-five rounds in the session, their performance got fairly even. In the first session, the start times were mostly above 2 minutes. In the second session, only two rounds' time were above 2 minutes, showing that in the two weeks between the sessions, they retained most of the information about the task. By analysing the times, other information can be obtained.

The time data presented in Table 1 shows the participant performance across the two sessions in the experiment. A general trend of improvement can be observed: for nearly all participants, the average task completion time (t_{mean}) decreased in the second session. This indicates that participants became more efficient as they became familiar with the task and the simplified instructions. Besides the mean times, the standard deviation of the task completion times (t_{std}) dropped significantly in the second session for every participant. This means that their consistency increased. For example, Participant 7's standard deviation dropped from 42.46 to 18.07 seconds, which shows significant improvement. The minimum and maximum completion times (t_{min} and t_{max}) showed a sim-



(a) First session's learning curves

(b) Second session's learning curves

Fig. 4: Learning curves during the experiment

ilar pattern. Most participants completed the tasks more quickly and within a narrower time frame during the second session.

A notable exception is Participant 1, whose average time slightly increased (from 73.25 to 73.85 seconds), but their standard deviation lowered from 12.91 to 4.62 seconds. It is possible that because of familiarity with similar tasks, they improved less as can be seen from their max time, which was way lower in the first session than other participants'. While they may have not improved in the second session, they executed the task with greater consistency.

A Wilcoxon signed-rank test was conducted to compare task completion times between Week 1 and Week 2. The results indicated a statistically significant improvement in performance ($W = 35.0$, $z = 2.38$, $p = 0.016$). Prior to this, a Shapiro–Wilk test confirmed that the distribution of differences did not deviate significantly from normality ($W = 0.861$, $p = 0.123$), supporting the robustness of the test. These results suggest a clear learning effect between sessions.

Overall, the results show that participants became faster, more accurate, and more consistent as they progressed through the rounds and the sessions.

4.3 Analysis of performance improvement with merged instructions

The hypothesis 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 but longer, detailed instructions help in the beginning.

Participant	1	3	5	6	2	4	7	8
t_{mean1}	73.25	101.24	82.63	108.38	92.11	97.58	126.03	116.07
t_{mean2}	73.85	72.19	69.50	72.33	68.07	67.30	99.38	89.37
t_{std1}	12.91	27.25	21.73	42.46	18.15	26.25	22.84	32.45
t_{std2}	4.62	13.68	11.32	18.07	7.83	12.25	7.39	17.25
t_{min1}	59.02	77.79	65.35	78.12	74.25	69.15	110.64	90.67
t_{min2}	65.70	60.20	56.99	59.22	56.93	53.59	92.17	77.70
t_{max1}	97.37	177.27	142.87	222.67	140.46	166.92	192.96	215.07
t_{max2}	81.49	112.17	98.96	127.16	87.68	98.92	119.69	140.73

Table 1: The time data from the experiment. The grey background indicates Group A, the white background indicates Group B.

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 2: Average time for each task

In Table 2, it can be seen how much time each task took on average. In the short version, these related actions were combined, reducing the instruction count to 5 tasks, which can be seen in Table 3. The merged, short instructions were created from two, three, or four semi-detailed instructions.

Short	Semi-detailed
1.	1. - 2.
2.	3. - 4. - 5.
3.	6. - 7. - 8. - 9.
4.	10. - 11.
5.	12. - 13.

Table 3: The task numbers that were merged

The results can be seen in Table 4. Participants who received shorter instructions completed the task faster during the first session, with an average time of 91.37 seconds, compared to 107.95 seconds for those using longer instructions. This suggests that some individuals were able to intuitively follow concise guidance without the need for detailed breakdowns. In the second session of the experiment, the group that had originally received longer instructions showed a more significant improvement. Their average time dropped to 69.30 seconds, while the short-instruction group achieved a slightly higher average of 71.97 seconds.

As shown in Tables 2–4, merged instruction steps appeared in later stages of the task and generally clustered low-effort actions (for example, part removal and placement) into single frames. This likely reduced the frequency of instruction switches and visual referencing, potentially lowering cognitive load.

Besides participants' time performance, errors were also recorded during both sessions to evaluate task accuracy. For most participants, the number of mistakes generally decreased between the first and second sessions. Group A made 8 errors initially, which dropped to 4 in the second session. Group B started with fewer errors (5), and also reduced them to 4.

For example, Participant 1 made two errors during the first session and none during the second. This suggests that participants not only became faster but also more precise as they became more familiar with the task structure and the simplified instruction format. Analyzing the types of errors revealed that the most common mistakes were dropping the screws, failure to change the screwdriver head and removing an incorrect screw. In total, five instances of screw

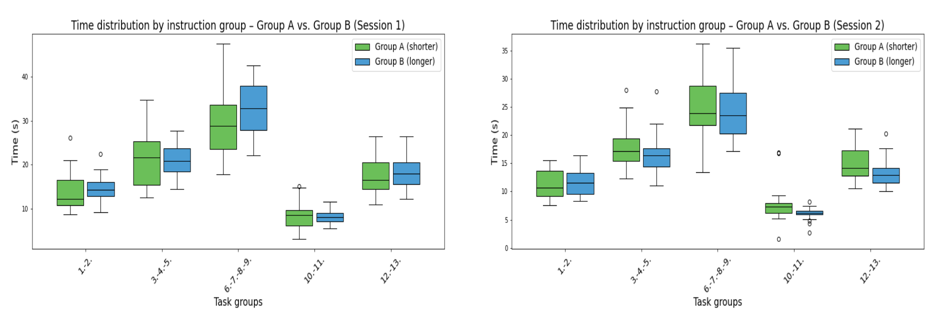
	t_{gmean1}	t_{gmean2}	t_{gmin1}	t_{gmin2}	t_{gmax1}	t_{gmax2}
Group A	91,37	71,97	59,02	56,99	222,67	127,16
Group B	107,95	69,30	69,15	53,59	215,07	140,73

Table 4: Time data in the two groups

drops and four instances of missed head changes occurred during the first session, while these numbers dropped to four and one respectively in the second session. The order of removing the fuse and the metal plate was a bigger mistake and it only got mixed up in Group A by two people in the first session, because in the short instruction set they were both on one page and it was easier to mess up and not pay attention as opposed to the semi-detailed version, where the instruction images were after one another so it was harder to get confused. Errors were categorized as omissions (e.g., skipping a screw or part) or commissions (e.g., incorrect placement). Omission errors decreased more significantly between sessions, indicating that routine steps were internalized. Commission errors remained mostly stable, reflecting persistent challenges with spatial reasoning and tool handling. This improvement further supports the learning effect observed through the time metrics. Simplifying the instruction set did not increase the number of errors; in contrast, fewer errors were committed after the transition to the shorter format, suggesting that participants effectively internalized the task sequence. This finding indicates a positive shift in the speed-accuracy trade-off as participants became more familiar with the process.

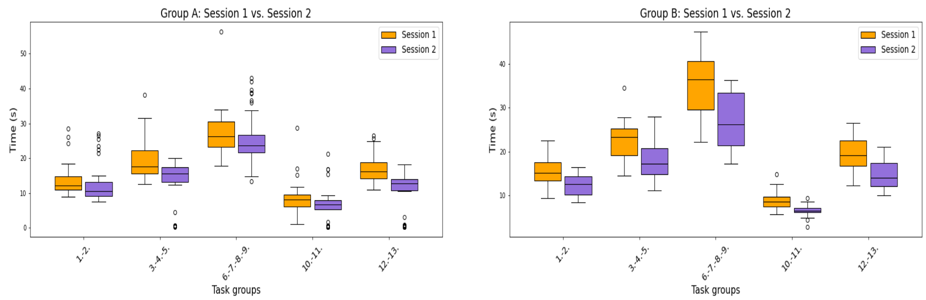
These results support the assumption that starting with detailed instructions provides a more solid foundation for learning. Group B, which began with the semi-detailed instruction set, showed a sharper performance improvement and lower error rates in the second session, suggesting that initial clarity helped them more easily understand the task.

Figures 5 and 6 present boxplots illustrating task completion times in both sessions and across both participant groups. These visualizations provide additional insight into the performance distribution, variation, and improvements that occurred due to instruction simplification and repetition. Figures 5 compares the overall performance in the two sessions. In the first session, as seen in Figure 5a, the boxplots show a wide range of completion times with several outliers, indicating variability in participant performance and a higher cognitive load when the task was still unfamiliar. The session after two weeks, shown in



(a) Boxplot from the first session (b) Boxplot from the second session

Fig. 5: Boxplots of the two sessions



(a) Boxplot from Group A (b) Boxplot from Group B

Fig. 6: Boxplots from the two groups

Figure 5a reveals more compact boxes and shorter whiskers, suggesting that participants completed the task more consistently and with fewer extreme delays.

Figure 6 breaks this down by group. Group A is shown on Figure 6a, which started with the short version of the instructions, exhibited relatively lower variance even in the first session. This implies that some participants could adapt quickly to minimal instructions, perhaps due to intuition or prior experience. Group B (seen on Figure 6b), who did their first session with the semi-detailed instructions, showed greater variance in the first session but a more significant improvement in the second. Their boxplot becomes much narrower, aligning closely with Group A's performance, indicating successful adaptation and internalization of the task flow. Together, the figures highlight that while minimal instructions may work well for some participants from the beginning, starting with more detailed guidance can better support others in building a robust mental model of the task. In both cases, by the second session, the performance became more stable and efficient, confirming the positive impact of instruction simplification and practice over time.

5 Conclusion

This study explored how simplifying work instructions influences operator performance and learning during a repetitive disassembly task. Using two instruction types, one semi-detailed and one short. We observed that once the task structure was understood, simplified instructions supported faster and more consistent task execution without increasing errors. Participants improved across sessions regardless of the initial instruction type, highlighting the potential of gradually reducing instruction detail after familiarization. These findings align with cognitive load theory, suggesting that instruction abstraction can enhance efficiency once a mental model is formed. While the results are promising, this research is best viewed as an exploratory study or proof of concept. The small sample size ($n = 8$) and controlled lab setting limit broader generalization. Nonetheless, the experiment demonstrates a viable method for testing instruction strategies and reveals performance trends worthy of further investigation. These insights suggest that training could begin with detailed guidance and then shift toward simplified instructions to optimize learning and execution time. Future work could examine how other instruction formats, such as animations or icons, interact with task familiarity and abstraction level to affect operator performance.

This work has been implemented by the TKP2021-NVA-10 project with the support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the 2021 Thematic Excellence Programme funding scheme.

Acknowledgments. M. Gugolya is supported by the Egyetemi Kutatói Ösztöndíj Program (2024-2.1.1-EKÖP), a national excellence program of the ministry for culture and innovation from the source of the national research, development and innovation fund.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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