IET Collaborative Intelligent Manufacturing

WILEY

The Institution of Engineering and Technology

ORIGINAL RESEARCH OPEN ACCESS

Assessing the Learning Curve of Human Operators Under Verbal Distraction

Mónika Gugolya[1] | Tibor Medvegy[1] | János Abonyi[2,3] | Tamás Ruppert[1,2]

[1]Department of System Engineering, University of Pannonia, Veszprém, Hungary | [2]HUN-REN-PE Complex Systems Monitoring Research Group, University of Pannonia, Veszprém, Hungary | [3]Department of Process Engineering, University of Pannonia, Veszprém, Hungary

Correspondence: Tamás Ruppert (ruppert.tamas@mk.uni-pannon.hu)

Received: 17 March 2025 | **Revised:** 23 June 2025 | **Accepted:** 30 June 2025

Handling Editor: Salvatore Digiesi

Funding: 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.

Keywords: distraction | human computer interaction | human performance | learning curve | manufacturing systems

ABSTRACT

This study investigates the learning curve in an assembly process under distraction, highlighting the use of video-based monitoring to evaluate changes in human performance over time. The experimental setup involving camera- and timer-based monitoring to evaluate operator performance in different metrics, including time-based indicators and accuracy of the assembled product. Participants were tasked with replicating patterns until they got a flat learning curve without any distractions during the process. After learning the process, they were also asked to repeat the task with conversation-based distractions to assess its influence during the main task. In our developed framework, an ArUco marker-based video recognition enabled the accuracy assessment. Statistical analyses of the collected data provided insight into performance variations. The study evaluates changes in the learning curve during verbal distraction, highlighting the need to understand and consider its effect during the process. The experiments revealed significant effects of distraction on the completion time, but the camera-based recognition system showed no notable decline in work quality.

1 | Introduction

The skills gap and labour shortage are pressing issues that emphasise the importance of understanding and addressing learning curves. It is important to discuss the ambiguity and challenges in defining and measuring skill gaps. The fourth industrial revolution involves the integration of digital technologies in industrial processes, which has significantly transformed the skills requirements of the workforce [1]. Speed and accuracy in completing tasks are the main performance metrics for human workers. When focusing on the speed aspect of a repetitive task, individuals tend to become faster with each repetition. This can be observed by plotting a scatter graph of time per repetition against the repetition number. The trend line that fits these data points, known as a learning curve, was first proposed by Wright [2]. Learning curves have served as valuable management tools [3], enabling prediction and monitoring of performance at multiple levels and in various areas, such as manufacturing, education, banking, and many more [4]. The occurrence and characteristics of human learning and forgetting are extensively studied across various fields. Learning curves in production and operations management describe workers' performance improvements due to repetition or experience. This concept is particularly relevant for labour-intensive manufacturing firms, especially where labour costs are high [5].

Several factors can influence the shape and steepness of the learning curve. Learning is often modelled as a combination of cognitive and motor elements [6]. These factors shape the learning curves [7] and highlight differences between low-fidelity and high-fidelity simulations. For example, training time [8] is a significant measure. In ref. [9], they used different training systems and compared them and their effect on the learning curve. Another factor affecting learning can be the complexity of the task [10]. In their study [11], the authors found that member turnover and task complexity are vital predictors of group productivity gains. Both variables significantly affected productivity, which increased as groups gained experience over time. The concept of learning curves has evolved significantly since Wright's introduction. This foundational model demonstrated that production time decreases constantly with each doubling of produced parts. Over time, estimating learning curve parameters has become crucial for categorising production runs or batches and understanding the behaviour of similar processes. Technological advances have provided new data collection methods, which improve traditional learning curve theories [12]. Gender also has an impact on the learning curve. Ben-Gal et al. [13] found that female dental students outperformed male students in motor learning tasks, particularly during the initial weeks and the final assessment of a 12-week manual skills course. Kostiuk and Follmann [14] observed that female recruiters performed slightly better than their male counterparts. At the same time, academic background had no positive effect on performance and, in some cases, higher education was associated with lower productivity.

The ability to perform multiple tasks simultaneously is limited [15]. Disruptions during the learning process can significantly impact task performance. Immediate interruptions cause the most errors and slowdowns, while negotiated and mediated interruptions reduce errors and are less disruptive. Scheduled interruptions result in slower performance but fewer errors than immediate interruptions [16]. Frequent interruptions also have an effect on the quality of the work [17].

Verbal distractions have an impact on working memory and attentional processes. Recent studies have shown that irrelevant speech significantly impairs visual-verbal serial recall performance, particularly when the speech is meaningful and variable [18]. Recent studies indicate that individuals frequently underestimate the disruptive effects of familiar or fluent speech on cognitive tasks, primarily due to the processing-fluency heuristic [19].

Various physiological sensors and machine learning-based algorithms can help optimise task allocation and reduce cognitive load [20]. It is valuable to see how different methods of presentation of material and information affect assembly time and workload. Better organised materials and visual instructions can enhance efficiency and reduce stress in manual assembly tasks [21]. Carvalho et al. [22] highlight that cognitive manufacturing focuses on reducing mental workload through digitalised work instructions, real-time analytics dashboards, and augmented reality interfaces. Sensors, Internet of Things, and Artificial Intelligence can also optimise workload and improve worker well-being [23]. It is important to consider the cognitive interference experienced when transitioning from one repetition to the next during the learning process [24].

TABLE 1 | Comparison of related studies by learning (L), distraction (D), realism (R), and accuracy (A).

Study	L	D	R	A
Ben-Gal et al. [13]	Y	—	Y	—
Kolbeinsson et al. [16]	—	Y	Y	—
Leist et al. [18]	—	Y	—	—
Zickerick et al. [25]	—	Y	—	—
Jaber and Glock [4]	Y	—	—	—
Carvalho et al. [22]	—	—	Y	—

Several studies have addressed different aspects of human performance, learning, and task disruption. However, few have integrated these elements into a unified framework. While learning curves have been extensively studied in manufacturing, training systems, and motor learning tasks, the inclusion of cognitive distractions in experimental designs remains limited. Moreover, most studies do not incorporate objective, visual-based accuracy measurements, nor do they use real-world assembly tasks as part of their experimental protocol. To position our work within the existing body of research, Table 1 summarises key prior studies and highlights their focus areas. The table shows whether the studies addressed (Y) learning curves (L), included distractions (D), used real-world tasks (R), and evaluated spatial accuracy (A).

Our study introduces a comprehensive experimental setup using camera monitoring and ArUco markers to precisely evaluate task accuracy and time efficiency. We developed an approach to assess the impact of distraction and its subsequent effect on task performance by evaluating the learning curve. The study underscores the importance of practice in improving performance, offering valuable insights into how skill acquisition can be optimised over time. The findings of this research contribute to a broader understanding of cognitive load management and human efficiency in manual assembly tasks, offering practical implications for improving productivity and accuracy in such environments.

This study aims to address these gaps by proposing a framework that evaluates human learning efficiency under distraction with both time-based and visual accuracy metrics using marker-based computer vision systems such as ArUco tracking.

Following this introduction and the literature review, in Section 2 the hypothesis and experiment design will be presented. Section 3 shows the developed video-based evaluation method. In Section 4, the findings and results from the experiment are detailed. The paper concludes with a synthesis of findings in Section 5.

2 | Hypothesis and the Design of Experiment

Our study aims to assess the effect of verbal distraction on the human learning curves while participants perform a specific task repeatedly. Zickerick et al. [25] investigated the differential effects of interruptions and distractions on working memory using ERP (Event Related Potential) analysis, and found that even task-irrelevant distractions can alter subsequent attentional allocation. Their findings support the idea that both foreknowledge and the type of interference affect the availability of attentional resources. This justifies our focus on verbal distractions that mimic everyday low-level interruptions, as they are most similar to real work environments where people interact verbally with one another in group settings.

The developed experiment investigates how individuals learn and improve their performance over time, particularly in tasks requiring precision and speed. We aim to measure the time it takes participants to complete a given task and the accuracy of their performance with and without additional distraction. By analysing these metrics, we can determine each participant's learning curve, indicating how quickly they can master the task. We also want to observe how much it changes after they have learnt it, if they are disturbed (as a secondary task) by an oral questionnaire. We formulate two hypotheses for the study:

- **H1**—The quality of the work will be reduced due to the distraction.
- **H2**—The completion time will increase due to the distraction

2.1 | Participants

Seventeen people participated in the experiment. Eight of them were female, and nine of them were male. All of them have academic backgrounds; they were either researchers or students. The participants ages ranged from 18 to 38, with an average of 25.82 and a standard deviation of 5.69. All participants first encountered the task during the experiment; they only knew they had to build something with blocks, but the shape and the pattern were unknown. All the participants provided their consent.

2.2 | Experiment Design

The use case is presented through a pattern-building process. It was chosen because, in a relatively short time, the participants could learn it, and the quality assessment could be performed automatically.

Others have used pattern building as part of their experiment. The Block Design Test, introduced by Kohs [26], is a classic example of a pattern replication task used to assess nonverbal intelligence. Participants recreate complex geometric patterns using coloured cubes. Landau et al. [27] examined children's step-by-step constructions using Lego blocks. They discovered that even young participants followed a systematic, layer-by-layer building approach, emphasising stability and efficiency. These findings align with our focus on learning dynamics, although their analysis did not consider time pressure or external distractions.

The fixed pattern (shown in Figure 1) is presented to the participants who were required to replicate it. The experiment was carried out in the Industry 5.0 laboratory of the University of Pannonia. Each session was designed to last approximately 30 min, which allowed each participant to complete the task comfortably. In Figure 2, the experiment setup can be seen. A laptop was placed in front of the participants, showing the pattern that needed to be built. The whole assembled pattern was shown. The pieces were always in the same spot, with four pieces on the left and four on the right side of the participant. They could grab and place the pieces in an order they preferred with both hands, only the final pattern was specified. They had to build the pattern over black paper, which had four red circles on the corners to help with the quality assessment. A mobile phone was also there to record the time, the participants put the phone in a suitable place for them.

The pattern design is formed using eight cubes of various shapes. Participants are introduced to this pattern at the experiment for the first time. The participants repeatedly perform the same task. They continue assembling the pattern until they consistently complete the task in nearly the same amount of time. This steady performance signifies mastery of the process, as participants become skilled at arranging the cubes as required. Familiarity with the cube locations enables participants to develop strategies and optimise their approach.

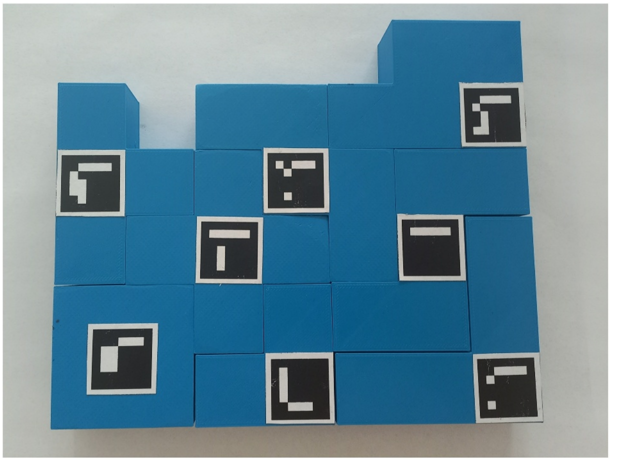


FIGURE 1 | The predefined pattern of the building process.

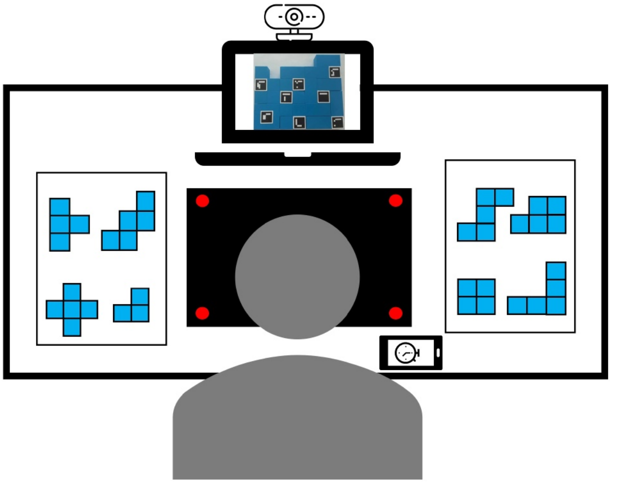


FIGURE 2 | The setup of the experiment.

The participants were sitting at a table where they assembled the pattern. A camera was looking above the area to take a picture of the finished pattern. The experiment process consisted of two parts, as seen in Figure 3. First was the training phase, where they repeated the pattern without any interruptions at least 20 times, and we got a learning curve from it. After that was the distraction phase, where they were asked 10 questions that they had to answer as a secondary task during the building in 10 rounds. During this distraction phase, the participants were subjected to interruptions during the pattern-building task to assess the influence of disturbances on performance. Distractions included verbal enquiries (see Appendix A) and required participants to respond while maintaining focus on the task. The aim was to observe how the distraction as a secondary task affected completion time and pattern accuracy. As detailed in the Appendix A, participants were asked about collaboration and relationships with robots. The standardised set of 10 questions ensured similar conditions between all participants. The role of the questions was only to distract the participant from their task, so they had to think about their answers.

2.3 | Recorded Measures and Processing Methods

We measured performance and quality of work during both phases of the experiment. The timing process involved participants starting and halting the stopwatch on their own. A mobile phone was used with the aTimeLogger application [28]. Before they began, they started the timer, and after they placed the last piece, they pressed it again. Evaluating time is crucial because it directly reflects the efficiency and performance of the participants under different circumstances. By analysing the times, we can quantify the impact of distractions on task performance.

In the experiment, the number of attempts at which the learning phase ended was observed. This helped determine the point where the participants had become proficient in the task. The average time taken in the learnt phase without any distractions was also calculated, providing a baseline for performance under ideal conditions. Additionally, the average time taken during distractions was calculated to evaluate how interruptions affected task completion times. The main variable of the experiment was the measurement of distraction versus non-distraction. The objective was to investigate the impact of this variable on the quality of the work and the time required to complete the pattern.

Quality is also an important indicator, the method about how we assessed it is explained more in the next section. This accuracy metric is meaningful in our context for several reasons. The task is spatial and visual; accurately placing the cubes demonstrates cognitive understanding and motor execution of the learnt pattern. Small misalignments, although not necessarily indicative of complete failure, can reveal how distractions affect fine-motor coordination and attention to detail. Furthermore, since the task was repeated until participants exhibited a plateau in performance, deviations from the reference pattern serve as an objective, quantifiable indicator of degraded performance during distraction. The use of angles and distances between the pieces/markers allows a more subtle and scalable assessment than a simple yes/no evaluation, allowing the detection of subtle quality degradations that may result from increased cognitive demands during distractions.

In our study, statistical data analysis is crucial in understanding the learning curves and performance under distraction. We used t-tests to compare performance metrics such as completion times and accuracy between the learning and distracted phases. The cut-off points for identifying the learning phase were determined by visual inspection.

3 | The Developed Video-Based Evaluation Method

Each cube is marked with an ArUco code attached to its top surface (see Figure 1), allowing the camera to recognise whether the pattern has been correctly assembled. Each ArUco code is associated with a unique numerical identifier, which can be identified using the corresponding OpenCV library. The

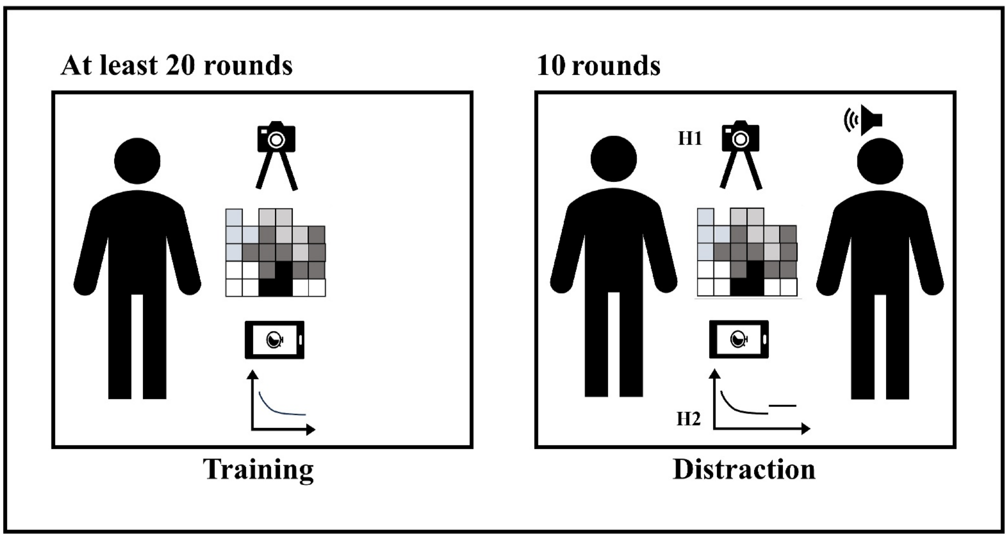


FIGURE 3 | The process of the experiment.

integration of ArUco codes serves a dual purpose. Firstly, it verifies whether the pattern has been successfully reproduced. Secondly, it provides a means of assessing the accuracy of the participant's arrangement. In the images, the locations of the markers were determined, and the pixel coordinates were obtained from these. To achieve this precision assessment, a reference image is initially created. A specific cube is selected as the anchor point. The angles at which the other cubes are arranged are calculated relative to this anchor point (see Figure 4). This reference data serves as a reference for evaluating subsequent attempts.

Using the obtained pixel coordinates, the angles and distances were calculated. The four red dots in the corners of the work area (see Figure 4) help reduce each picture to this area so that distances can be compared. A reference point mentioned previously is the cube marked with the marker 2 in the bottom left corner. In addition, an image was created where the pattern was perfectly arranged (the reference image), and the ones made by the participants were compared with this. $\mathbf{p_i}$ and $\mathbf{p_r}$ are the individual 2D positions of the markers, $\mathbf{p_i}$ pointing to the individual points ($i = 1 \ldots N$, where N is the number of pattern elements), while $\mathbf{p_r}$ points to the reference. By subtracting these, we obtain a vector $\mathbf{v_i}$

$$\mathbf{v_i} = \mathbf{p_i} - \mathbf{p_r} \tag{1}$$

and the angle of $\mathbf{v_i}$ is calculated (α_i), where x_i is the x-direction component of $\mathbf{v_i}$:

$$\alpha_i = \arccos\left(\frac{x_i}{|\mathbf{v_i}|}\right) \tag{2}$$

Reference angles are also calculated for the perfect pattern (β_i) using the same method. The reference angles and the calculated angles were subtracted from each other to get the d_i as a deviation from the reference product:

$$d_i^{(a)} = \alpha_i - \beta_i \tag{3}$$

The mean of the deviations of all the N elements $(\overline{d})$ is calculated. The standard deviation of these angular deviations is as follows:

$$\sigma_a = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(d_i^{(a)} - \overline{d}^{(a)}\right)^2} \tag{4}$$

Similarly, the distance between each participant marker and its reference is as follows:

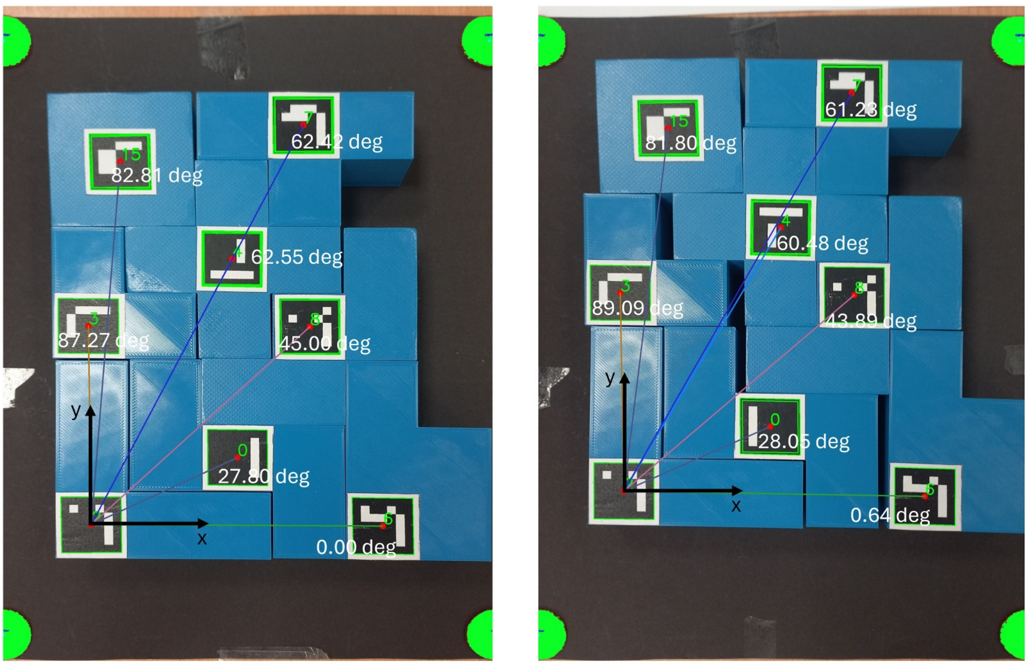
$$d_i^{(d)} = \left\| p_i - p_r \right\| \tag{5}$$

The standard deviation of these distances is as follows:

$$\sigma_d = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(d_i^{(d)} - \overline{d}^{(d)}\right)^2} \tag{6}$$

This approach ensures a more prices and automatic evaluation, capturing subtle variations that may not be apparent when assessing distances or angles alone.

To validate the described quality assessment method, a series of pictures of different completed patterns was created. Each was slightly worse than the previous one, and the last two patterns were built in a wrong way. The standard deviations were calculated for these pictures as described previously. After trying different combinations, multiplying the two deviations, the standard deviation of the angles (σ_a) and the standard deviation of the distances (σ_d) together gave the same order of the



(a) A well-built pattern

(b) A less accurately built pattern

FIGURE 4 | Comparison of patterns.

built patterns and this gave us the quality (Q). If the Q value is low, it means the pattern is well assembled; if it is higher, then it is not as good.

To exclude the limitations of the multiplicative quality metric, we introduce a weighted formulation that provides greater interpretability and avoids the nullification effect when either deviation is zero. The quality metric Q is defined as a combination of the angular and distance standard deviations:

$$Q = 0.5 \cdot \sigma_a + 0.5 \cdot \sigma_d \tag{7}$$

4 | Results and Discussion

During our experiments, 17 participants assembled a pattern as seen in Figure 1. Participants were required to replicate the pattern at least 20 times in a controlled environment without any distractions. Afterwards, they repeated the task 10 times while responding to questions asked (as a secondary task). After each round, pictures of the completed patterns were taken for the quality analysis as described in the previous section.

After evaluating the images, we categorised them into four groups according to the standard deviation as the quality of the constructed pattern. The groups consist of perfectly constructed patterns indicated with 1, good with 2, slightly flawed with 3, and completely incorrect with 4. The limits can be seen in Table 2. These limits were determined using the qualities of the reference picture series. With this approach, real-time analysis can be performed on the arrangement.

As a demonstration, Figure 4 shows two images, one representing a well-assembled pattern, and the other displaying a less accurate assembly. Markers in these images were analysed and the standard deviation of angles, when subtracted from the reference, provided insights into the patterns' spatial accuracy. The Q of the well-assembled pattern was blue 2.09, indicating a tight cluster of blocks, which belongs to Group 2. However, the less precise pattern showed a higher Q value of 3.86, indicating a greater spread of angles and, hence, a less accurate assembled pattern, and it belongs to Group 3.

The difference in results emphasises how distractions can affect one's ability to complete a task effectively. In particular, the time required for the initial completion of the pattern ranged from 20 to 30 s, gradually decreasing to approximately 10–15 s over subsequent attempts, indicating a learning effect and improved efficiency. The cut-off points for the learning curves were determined individually for each participant. The difference between each consecutive attempt were calculated, and where this stayed consistently around plus or minus 2 s, that was determined the 'learnt' phase. The learnt phase is typically initiated around the 15th attempt, and participants consistently achieve the pattern within a fixed time frame after the 17th attempt. Figure 5 shows the times of each round for each participant. The overall learning can also be seen on this figure as after the 13th attempt the curve is relatively flat. In Figure 6, it can be seen how the times between the different phases looked. The light grey shows the times after learning and during distraction, and most of these are between 10 and 20 s. The darker grey shows the times during each participants 'learnt' phase.

Thirteen out of 17 participants exhibited decreased performance during the secondary task (under distraction), and three participants maintained or improved their performance while answering questions as seen in Table 3. This may be because the number of learning tests was not enough for them to learn, so they could improve even more during distraction. The standard deviation was mostly between 1 and 3 s. In addition, the analysis included a comparison of the average time taken during the distraction phase with that during the learning phase. The results showed that the average time of all participants during disturbances exceeded their best completion time. The difference ranged from 6% to 46%, emphasising the varied impact of disturbances on individual performance. These results highlight the complex relationship between human thinking, task performance, and external distractions.

The quality of the patterns of the participants was analysed. As we described in the previous section, the assessment involves calculating the angles between recognised markers in the assembled patterns relative to a reference marker that measures the distances between markers due to potential misalignments and provides a robust measure of pattern quality.

As mentioned above, the quality was calculated by multiplying the two deviations by 0.5 and then summarising them; this gave a number for each image. Based on these, four groups were

TABLE 2 | The limits of the quality groups.

Group	Lower limit	Upper limit
1	0 ≤	< 1.45
2	1.45 ≤	< 2.45
3	2.45 ≤	< 3.45
4	3.45 ≤	—

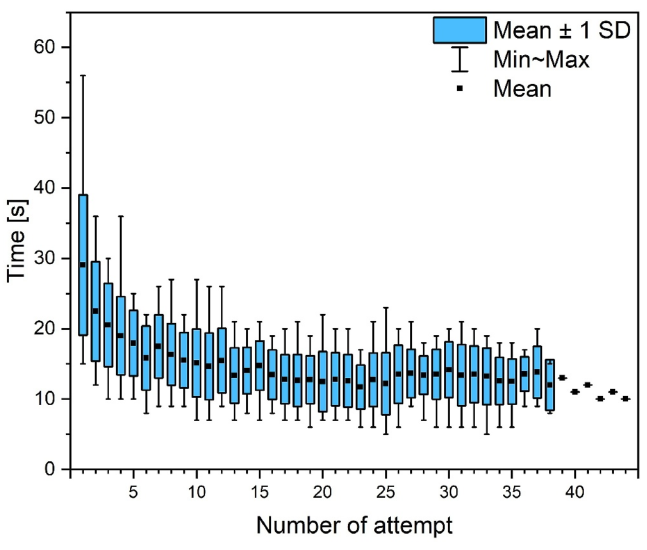


FIGURE 5 | The times for each round.

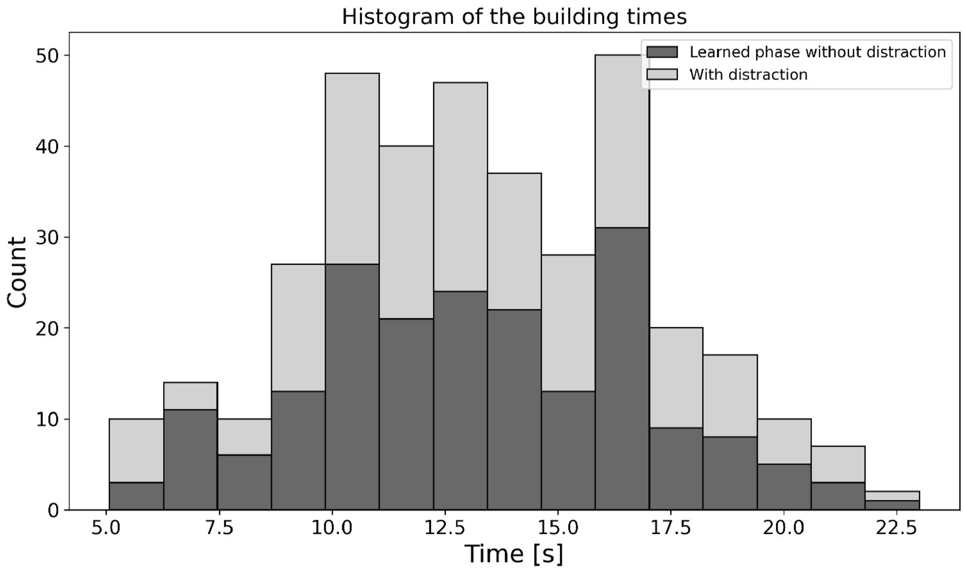


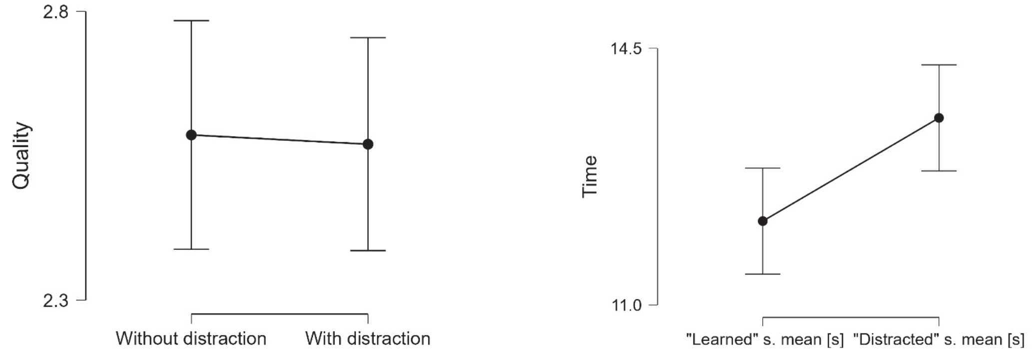
FIGURE 6 | The times it took to build the pattern during the experiment's 'learnt' and 'distracted' phase.

TABLE 3 | The means and standard deviations of the participants' building times and qualities.

	Time				**Quality group**			
	'Learnt' phase		**With distraction**		**'Learnt' phase**		**With distraction**	
ID	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
1	17.40	2.01	19.20	1.93	1.45	0.69	1.50	0.71
2	12.64	2.21	12.70	1.34	1.62	0.77	2.20	0.79
3	17.47	1.23	17.00	1.15	1.53	0.64	1.56	1.01
4	14.93	1.49	18.20	2.04	1.88	0.96	2.40	0.84
5	12.55	1.86	14.00	1.49	3.27	0.65	2.10	1.20
6	13.65	1.66	11.90	1.29	1.94	0.68	1.71	0.95
7	18.63	2.28	14.20	1.03	1.87	0.92	1.90	0.88
8	7.42	0.79	8.80	0.92	2.64	0.81	2.80	1.03
9	11.50	1.64	12.78	1.79	2.83	0.41	2.11	0.78
10	13.27	1.10	15.60	2.07	2.83	0.75	2.43	0.79
11	15.55	1.75	16.70	1.89	2.58	0.67	1.67	0.87
12	10.56	0.81	12.41	1.43	4.00	0.00	4.00	0.00
13	12.78	1.06	16.47	3.26	3.75	0.62	3.60	0.52
14	6.66	0.66	6.24	1.08	3.00	—	3.14	1.07
15	9.49	0.78	9.62	1.10		—	4.00	0
16	11.58	0.92	12.78	1.25	3.60	0.70	4.00	0
17	9.66	1.16	10.13	0.75	—	—	—	—

created. The groups are categorised as described in the previous section. As illustrated in Figure 7a, there was just a slight difference in pattern quality between the standard phase and the distracted phase; however, there was almost no difference (a higher value indicates lower quality). However, our hypothesis (H1) is not supported by this.

A paired *t*-test was conducted on the average completion times of the participants during the learnt phase (without distraction) and the distraction phase as seen in Figure 7b. Before conducting the test, the Shapiro–Wilk test was used to evaluate the normality of the differences in task completion times and quality scores. Both datasets satisfied the normality assumption ($p = 0.089$ for time and $p = 0.298$ for quality), justifying the use of the parametric test. The *p*-value, a key determinant in hypothesis testing, was found to be 0.01. This value signifies that the likelihood of observing such a difference by random chance is less than 5%, which falls below the



(a) Comparison of means of the quality groups between the normal and distracted phase

(b) Comparison of the ”learned” and ”distracted” mean times

FIGURE 7 | Comparison of different metrics between distracted and nondistracted phases.

conventional threshold of 0.05. Consequently, the null hypothesis can be confidently rejected, affirming a statistically significant difference between the completion times under normal and distracted conditions.

This significant *p*-value suggests that distractions have a measurable impact on participant performance, confirming quantitative observations of increased completion times and variability during the distracted phase. In conclusion, we can state that our second hypothesis (H2) is confirmed by the results of the experiment.

The complexity of the pattern-building tasks may influence how distractions affect performance. Based on prior findings (e.g., Nnaji and Gambatese [17]), we hypothesise that more complex tasks increase sensitivity to interruptions. In highly demanding tasks, even brief distractions could lead to a complete stop in task execution, as dual-tasking becomes less feasible. This suggests that complexity could amplify the negative effects of distraction, a direction worth exploring in future work.

Hypothesis 1 is rejected. *The pattern quality between the standard phase and the distracted phase showed minimal variation; the quality did not decline during the distracted phase.*

Hypothesis 2 is confirmed. *The significant p-value indicates that distractions significantly affect participant performance, verifying quantitative findings of completion times and variability during the distraction phase. Therefore, we conclude that our second hypothesis is validated by the experimental results.*

The study has some limitations. The number of participants was limited, and task complexity was not systematically varied. Furthermore, the controlled experimental setting may not fully reflect real-world distractions. Future research could examine how different levels of task complexity influence sensitivity to distraction, and whether similar patterns emerge in more naturalistic environments. Expanding the sample size and task types would also help confirm and generalise the findings.

In summary, the results of this study underscore the significant impact of distractions on task performance. The findings reveal that while pattern quality only slightly decreases under distraction, completion times and variability markedly increase, demonstrating the measurable effects of distraction load. The observed learning curve highlights how repeated practice can improve efficiency, but also how external interruptions can hinder this progress. These insights emphasise the importance of managing distractions to maintain performance quality, with implications for fields where precision and efficiency are essential, such as industrial environments.

5 | Conclusion

This study aimed to explore the effects of distractions, on the accuracy and efficiency of pattern replication tasks. The experiment involved 17 participants who assembled a predefined pattern multiple times, both in undisturbed conditions and while responding to questions. The results demonstrated an apparent learning effect, with participants' completion times decreasing significantly after repeated attempts. However, when distractions were introduced, completion times increased, indicating that interruptions affected task performance. These results align with previous research on the effects of cognitive load and task interruptions, such as the work by Kolbeinsson et al. [16], which demonstrated that immediate interruptions mostly impact efficiency rather than accuracy, as in our case, the interruptions were scheduled, the participants know that they have to answer the questions. Statistical analysis of completion times and pattern accuracy supports our hypothesis.

This study contributes to the current body of knowledge by bridging underexplored areas: it combines the evaluation of learning curves with cognitive load effects using verbal distraction, applies a repeatable manual assembly task in a lifelike setting, and introduces a marker-based computer vision method to assess spatial accuracy. These aspects are rarely studied together, especially with quantifiable metrics for both timing and quality. Future work could build on this by expanding the experimental setup to include tasks of varying complexity or duration, introducing other forms of distraction (e.g., visual or auditory), and further automating the quality assessment pipeline for real-time feedback in industrial applications.

Author Contributions

Mónika Gugolya: data curation, investigation, visualization, writing – original draft. **Tibor Medvegy:** conceptualization, supervision, writing – review and editing. **János Abonyi:** conceptualization, writing – review and editing. **Tamás Ruppert:** conceptualization, methodology, supervision, validation, writing – review and editing.

Acknowledgements

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.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data available on request from the authors.

References

1. P. Rikala, G. Braun, M. Järvinen, J. Stahre, and R. Hämäläinen, "Understanding and Measuring Skill Gaps in Industry 4.0—A Review," *Technological Forecasting and Social Change* 201 (2024): 123206, https://doi.org/10.1016/j.techfore.2024.123206.

2. T. Wright, "Factors Affecting the Cost of Engineering," *Journal of the Aeronautical Sciences* 3, no. 4 (1936): 122–128, https://doi.org/10.2514/8.155.

3. C. Peña, D. Romero, and J. Noguez, "Parameterization Techniques to Support Human Learning Curves Forecasting & Optimization: Review, Method & Proposed Framework," *Computers & Industrial Engineering* (2024): 110314.

4. M. Y. Jaber and C. H. Glock, "A Learning Curve for Tasks With Cognitive and Motor Elements," *Computers & Industrial Engineering* 64, no. 3 (2013): 866–871, https://doi.org/10.1016/j.cie.2012.12.005.

5. C. H. Glock, E. H. Grosse, M. Y. Jaber, and T. L. Smunt, "Applications of Learning Curves in Production and Operations Management: A Systematic Literature Review," *Computers & Industrial Engineering* 131 (2019): 422–441, https://doi.org/10.1016/j.cie.2018.10.030.

6. J. Peltokorpi and M. Y. Jaber, "An Interference-Adjusted Power Learning Curve for Tasks With Cognitive and Motor Elements," *Applied Mathematical Modelling* 101 (2022): 157–170, https://doi.org/10.1016/j.apm.2021.08.016.

7. T. Viering and M. Loog, "The Shape of Learning Curves: A Review," *IEEE Transactions on Pattern Analysis and Machine Intelligence* 45, no. 6 (2022): 7799–7819, https://doi.org/10.1109/tpami.2022.3220744.

8. F. E. Ritter, M. K. Yeh, S. J. Stager, A. F. McDermott, and P. W. Weyhrauch, "The Effect of Task Fidelity on Learning Curves: A Synthetic Analysis," *International Journal of Human-Computer Interaction* 39, no. 11 (2023): 2253–2267, https://doi.org/10.1080/10447318.2022.2161863.

9. F. E. Ritter and A. F. McDermott, "The Effect of Task Fidelity on Learning Curves," in *Proceedings of the 18th International Conference on Cognitive Modeling (ICCM 2020)* (Applied Cognitive Science Lab, Penn State, 2020), 229–235.

10. D. A. Nembhard, "The Effects of Task Complexity and Experience on Learning and Forgetting: A Field Study," *Human Factors* 42, no. 2 (2000): 272–286, https://doi.org/10.1518/001872000779656516.

11. L. Argote, C. A. Insko, N. Yovetich, and A. A. Romero, "Group Learning Curves: The Effects of Turnover and Task Complexity on Group Performance," *Journal of Applied Social Psychology* 25, no. 6 (1995): 512–529, https://doi.org/10.1111/j.1559-1816.1995.tb01765.x.

12. C. Pena, D. Romero, and J. Noguez, "Workforce Learning Curves for Human-Based Assembly Operations: A State-of-the-Art Review," *Applied Sciences* 12, no. 19 (2022): 9608, https://doi.org/10.3390/app12199608.

13. G. Ben-Gal, L. Katorza, E. I. Weiss, and A. Ziv, "Testing Motor Learning Curves Among Dental Students," *Journal of Dental Education* 81, no. 10 (2017): 1171–1178, https://doi.org/10.21815/jde.017.076.

14. P. F. Kostiuk and D. A. Follmann, "Learning Curves, Personal Characteristics, and Job Performance," *Journal of Labor Economics* 7, no. 2 (1989): 129–146, https://doi.org/10.1086/298202.

15. H. Pashler, "Dual-Task Interference in Simple Tasks: Data and Theory," *Psychological Bulletin* 116, no. 2 (1994): 220–244, https://doi.org/10.1037/0033-2909.116.2.220.

16. A. Kolbeinsson, P. Thorvald, and J. Lindblom, "Coordinating the Interruption of Assembly Workers in Manufacturing," *Applied Ergonomics* 58 (2017): 361–371, https://doi.org/10.1016/j.apergo.2016.07.015.

17. C. Nnaji and J. A. Gambatese, "Worker Distraction Impacts on Safety and Work Quality: An Energy Component," in *Construction Research Congress 2016* (American Society of Civil Engineers (ASCE), 2016), 3005–3014.

18. L. Leist, T. Lachmann, S. J. Schlittmeier, M. Georgi, and M. Klatte, "Irrelevant Speech Impairs Serial Recall of Verbal but Not Spatial Items in Children and Adults," *Memory & Cognition* 51, no. 2 (2023): 307–320, https://doi.org/10.3758/s13421-022-01359-2.

19. G. F. Komar, A. Buchner, L. Mieth, R. Van de Vijver, and R. Bell, "Evidence of a Metacognitive Illusion in Stimulus-Specific Prospective Judgments of Distraction by Background Speech," *Scientific Reports* 14, no. 1 (2024): 24111, https://doi.org/10.1038/s41598-024-74719-4.

20. A. Lambay, Y. Liu, P. L. Morgan, and Z. Ji, "Machine Learning Assisted Human Fatigue Detection, Monitoring, and Recovery," *Digital Engineering* 1 (2024): 100004, https://doi.org/10.1016/j.dte.2024.100004.

21. A. Brolin, K. Case, and P. Thorvald, "Cognitive Aspects Affecting Human Performance in Manual Assembly," in *Advances in Manufacturing Technology XXX* (IOS Press, 2016), 231–236.

22. A. V. Carvalho, A. Chouchene, T. M. Lima, and F. Charrua-Santos, "Cognitive Manufacturing in Industry 4.0 Toward Cognitive Load Reduction: A Conceptual Framework," *Applied System Innovation* 3, no. 4 (2020): 55, https://doi.org/10.3390/asi3040055.

23. J. Yang, Y. Liu, and P. L. Morgan, "Human-Machine Interaction Towards Industry 5.0: Human-Centric Smart Manufacturing," *Digital Engineering* 2 (2024): 100013, https://doi.org/10.1016/j.dte.2024.100013.

24. M. Jaber, J. Peltokorpi, C. H. Glock, E. H. Grosse, and M. Pusic, "Adjustment for Cognitive Interference Enhances the Predictability of the Power Learning Curve," *International Journal of Production Economics* 234 (2021): 108045, https://doi.org/10.1016/j.ijpe.2021.108045.

25. B. Zickerick, S. Thönes, S. O. Kobald, E. Wascher, D. Schneider, and K. Küper, "Differential Effects of Interruptions and Distractions on Working Memory Processes in an ERP Study," *Frontiers in Human Neuroscience* 14 (2020): 84, https://doi.org/10.3389/fnhum.2020.00084.

26. S. C. Kohs, "The Block-Design Tests," *Journal of Experimental Psychology* 3, no. 5 (1920): 357–376, https://doi.org/10.1037/h0074466.

27. B. Landau, E. Davis, C. S. Cortesa, J. D. Jones, A. L. Shelton, *Young Children's Copying of Block Constructions: Remarkable Constraints in a Highly Complex Task* (Johns Hopkins University, 2022).

28. A. Pro, "Atimelogger Pro: Time Tracking App," accessed February 10, 2025, https://atimelogger.pro/.

Appendix A: Questionary

1. Have you ever watched videos or played games that included robots?
2. Have you ever been close or in the same space with a robot before?
3. Have you ever worked with a robot before?
4. How do you feel about the environment, and what do you think about the workload?
5. Is the operation consistent and predictable?
6. Do you understand thoroughly the task requirements?
7. Do you think your skills are sufficient and helpful for the tasks?
8. Is the robot's presence pleasant to you?
9. Are you happy with your performance?
10. Are you ready to collaborate with this robot on more important tasks?