



Article

Eye-Tracking for Human Performance Assessment in Industry 5.0 Research

Dana Hamarsheh, Caden Edwards and Mary Fendley *

Industrial Engineering, Louisiana Tech University, Ruston, LA 71272, USA; dih001@latech.edu (D.H.); cde029@latech.edu (C.E.)

* Correspondence: mfendley@latech.edu

Abstract

In the new industrial revolution 5.0 era, manufacturing facilities with manual assembly have higher expectations, higher mass customization, and more human involvement, as well as including new digital technologies in smart workstations. Given these expectations, the cognitive load of manual assembly workers is increasing. Cognitive assessment systems are being added to manufacturing facilities to work in parallel with physical and sensory assistance systems to establish better work conditions for workers and better overall system performance. This paper presents an exploratory study using eye-tracking as an assessment system to identify potential locations of increased cognitive workload and errors to better understand where and how to employ assistance for workers to improve the manual assembly and inspection process. The results of this study indicate that the highest workload occurs with measuring and inspection tasks, and most errors occur during the assembly of parts, where their geometry impacts placement. It also demonstrates the feasibility of eye-tracking as a low-cost, integral part of the human–computer system in the assembly environment.

Keywords: Industry 5.0; eye-tracking; assembly; inspection; cognitive workload

1. Introduction

In today's modern and fast-changing assembly lines, driven by the implementation of the new Industry 5.0 (I5.0) in assembly systems, assembly lines are less linear, featuring higher complexity and customized mass production. Current industrial systems need to implement I5.0 principles into current systems via smart, adaptive support systems [1]. Manual assembly workers must increase cognitive processing to keep up with the integration of I5.0 concepts, which include but are not limited to mass customization, digitalization, and human involvement.

The mass customization and personalization of products create challenges for assembly operations, which must navigate the tradeoff between automated systems that are highly productive and manual systems that are more flexible. Mass customization adds more complexity to industrial operations, which needs to be studied at different levels. Industry 4.0, conceptualized by its novel technologies, enables both higher productivity and higher product personalization to be achieved simultaneously, but research findings highlight that people need to be considered the center of focus in Assembly 4.0 [2].

Currently, the Industry 4.0 concept is used to describe the connection between the current and new enabling technologies, such as big data and analytics, simulation, au-



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onomous robots, the industrial internet of things, cybersecurity, additive manufacturing, the Cloud, and augmented reality [3,4].

Research interests in Industry 4.0 include the improvements achieved by introducing new digital technologies and the frameworks that are developed to test the effects of applying such technologies [1]. Research also shows the progression when applying theoretical frameworks of Industry 4.0 to existing industrial environments and the effect of the new digital technologies required by Industry 4.0 [5]. I4.0 aims to establish a balance between productivity, quantity, variant diversity and flexibility. Moreover, it considers humans as an embedded element in the system and as a source of improvement rather than a cost. Moving forward, the I5.0 environment is characterized as human-centric, resilient and sustainable, and considers the worker as an investment rather than a cost [6]. The characteristics of the I5.0 environment include product mass customization, production rate and cycle time constraints, new technologies, and human involvement. There is an inherent complexity in mass customization that drives research in the operator-driven I5.0 systems.

Mark et al. established a three-step framework that illustrates an approach to implementing Industry 4.0 concepts in small- and medium-sized enterprises [7]. The first level of the model is where the functional requirements and features of I4.0 are defined, the design solutions are identified and the problem is decomposed. In addition, enabling technologies for applying I4.0 are defined at this level. The second level of the framework is the level at which pilot projects are established, use cases are defined, feedback is collected and testimonials from pilot projects are analyzed. The third level of the framework is where the results of the pilot projects are used for the implementation of the I4.0 at an operational level and the work is transferred from project status to the processing stage.

The study presented here applies levels 1 and 2 from this model to I5.0. This was designed as an exploratory study to understand the process of manual assembly from a cognitive ergonomics point of view to identify points at which cognitive assistance could be integrated due to higher workloads and potential for error. The general nature of the study is flexible so that the outcome can focus on answering questions about the process of manual assembly. A manual experiment was designed to choose the suitable I5.0 principles and elements that can be utilized in future work. In this experiment, participants assembled a toy car to simulate the general manual assembly task processes of manufacturing workers.

I4.0 calls for the integration of enabling digital technologies—such as sensors, data analytics, and human–computer interaction systems—into manufacturing environments to achieve higher productivity, flexibility, and human–system collaboration [3,4]. I5.0 extends this vision by placing the worker at the center, treating cognitive and physical well-being as integral to system performance [6,8]. Eye-tracking, as employed in this study, is precisely such an enabling technology: it provides objective, real-time data on operator cognitive state that can be used to drive adaptive assistance systems in smart workstations. Rather than blindly deploying cognitive assistance, the I4.0 implementation roadmap outlined by Mark et al. [7] requires that functional requirements are first established. The present study fulfills this role—identifying which assembly and inspection tasks generate elevated cognitive load and where errors cluster so that targeted assistance systems can be designed and deployed in a subsequent Level 3 implementation. In this way, the eye-tracking experiment is a necessary and foundational step within the I4.0/I5.0 structure.

2. Background

2.1. Cognitive Load in Manual Assembly

Cognitive ergonomics focuses on finding a balance between the cognitive capabilities and limitations of the human operator while still considering the quality of the work output [9,10]. The changes in current work systems that come with increased automation

have modified the demands of work to become more cognitive in nature, rather than physical [11]. Cognitive workload involves the process of perceiving and interpreting signals, and then performing the assembly work after deciding on a particular course of action [12]. Manual assembly requires pre-manufactured components that the worker uses to create a more complete product. This can be done at a workstation or on an assembly line, and generally coordinates with semi-automated systems to assist the operator [13]. Studies have explored how an understanding of cognitive load in manufacturing can lead us to design better workplaces for the operator and have categorized factors that might have impact on high cognitive loads [14–19]. All studies concerning the cognitive aspects of manual assembly aim to reduce cognitive load, understand the process from a cognitive point of view, and offer solutions that suit new assembly line styles.

2.2. Eye-Tracking and Cognitive Load

Many different physiological measures have been used to assess cognitive load, including cardiovascular and eye activity measures [20]; electrophysiological measures such as heart rate [21]; cardiovascular response during computer-mouse work [22]; using heart rate to measure cognitive load in program-running versus problem-solving tasks [23]; the prediction of perceived cognitive load from heart rate [24]; cognitive and emotional processes' monitoring through pupillary and cardiac data [25]; and eye measures such as blink frequency and duration in simulated flight tasks [26]. Eye-tracking was chosen for this study, as it can be integrated into the manufacturing process fairly unobtrusively, forming a key technological piece of the I5.0 environment [18,27].

Eye-tracking technology is one of the physiological measures that are increasingly being used in measuring operator cognitive load, especially in safety-critical applications [28–30]. It is utilized to understand and assist human performance in many fields, such as psychology [31], air traffic control and aviation [20,32,33], human–computer interaction [34], food industry [35], automation [36], and driving safety [37,38], and its use in engineering and manufacturing is increasing [39,40].

Technological advances create new challenges and require new technologies to be applied and tested in the workplace to improve operations [41]. Previously, companies and industrial facilities mainly focused on keeping up with the digitalization era by improving productivity, profitability and efficiency. Later, it was realized that improving labor conditions, working standards and methods on the shop floor is essential [42,43]. Eye-tracking was used to test the effect of several factors, including years of experience, past injury experience and training [44]. In engineering design, eye-tracking was used to understand the visual behavior of engineering designers and in engineering drawings [45,46]. Eye-tracking was used to assess different aspects of the manufacturing processes. It was used in the automotive industry to improve the quality control process by applying the technology in a real factory environment and analyzing output from eye signals [39].

Automation in construction also benefitted from eye-tracking technology to automate and personalize safety training and feedback for construction workers, and to enhance worker's safety by understanding viewing patterns [47]. In addition, it was successfully used to identify and classify construction equipment and operators' mental fatigue levels [48].

The use of eye-tracking is still relatively new in manual assembly applications due to the complex and interactive nature of manual assembly environment. However, it has many features that open doors for the increased involvement of this technology in the manual assembly system [27,40,49,50].

In a lean manual assembly company, eye-tracking video analysis was implemented as one of the ergonomic enhancement techniques for the work environment. Eye-tracking measures were integrated to improve the whole assembly process, reduce time and non-value-adding practices and enhance the ergonomic design of the workplace for the employees [41]. Eye-tracking systems can potentially reduce errors and increase productivity and efficiency in assembly processes [51,52].

Eye-tracking systems measure several different human parameters that serve as indicators of cognitive load. Li et al. employed measurements of pupil dilation, blink rate, fixation dispersion, and saccadic eye movements to capture cognitive load differences between in-motion and stationary environments [52]. Saiz-Manzanares et al. captured cognitive load during multichannel activities in university students using fixation count, fixation duration, average duration of fixation, saccade count, gaze point, pupil diameter, and the number of visits or revisits [53]. Yu et al. also measured cognitive load by using saccade duration, fixation duration, and number of saccades, in combination with fNIRS neuroimaging data [54]. Across these studies, fixation duration and fixation count were commonly used as reliable eye-tracking metrics for assessing cognitive workload.

The study investigates whether eye-tracking metrics can identify tasks within a manual assembly and inspection process that generate elevated cognitive workload. In the present study, two primary eye-tracking metrics are used to assess cognitive load: fixation duration and normalized fixation count. Fixation duration refers to the total time a participant's gaze dwells on a specific Area of Interest (AOI), with longer fixation durations associated with higher cognitive processing demands [8,55]. Normalized fixation count represents the number of fixations divided by the total fixation duration within each AOI, providing a measure of the frequency of visual attention allocation. These two metrics were selected because they are among the most widely validated eye-tracking indicators of cognitive load in manual assembly and inspection tasks, and because they can be captured unobtrusively using wearable eye-tracking hardware, without interrupting the assembly process.

2.3. Research Gap and Study Objectives

The studies reviewed above establish eye-tracking as a viable tool for cognitive load assessment across domains such as aviation, construction, and automotive quality control. However, much of this work was conducted in highly controlled, non-assembly settings or focused on overall process-level optimization rather than isolating the specific task types within a manual assembly and inspection process that generate elevated cognitive demand. Limited empirical work has applied eye-tracking metrics to identify task-level differences in cognitive workload within manual assembly, particularly within the context of I4.0/I5.0 implementation frameworks. This gap is significant because the adaptive, human-centric assistance systems called for by I5.0 require task-level diagnostic information to determine where cognitive support is most needed and what form that support should take [7,27]. The following research questions have been formulated to address this research gap:

- Does cognitive workload, as measured by fixation duration and fixation count, vary significantly across tasks within a manual assembly process?
- Do measurement tasks generate higher cognitive workload than attachment tasks during manual assembly?
- Is there a relationship between eye-tracking metrics and inspection error rates during the inspection phase?

These research questions are designed to provide the task-level cognitive load diagnostics necessary for designing targeted assistance systems within the I4.0/I5.0 implementation framework [7].

3. Materials and Methods

3.1. Study Design

The study is a within-subjects, single-session exploratory study. The study follows levels 1 and 2 of Mark et al.'s [7] framework, using eye-tracking as the primary cognitive load measure and the assembly task as a proxy for industrial manual assembly.

3.2. Participants

Thirteen participants (4 females and 9 males) within the age range of 18–25 ($M = 21.5$ years, $SD = 3.5$ years) participated in the study. Table 1 shows the participants' demographic information.

Table 1. Participants' demographic information.

Characteristic	Value
Total Participants	13
Female	4
Male	9
Age Range	18–25 Years
Mean Age	21.5 Years
Age SD	3.5 Years
Background	Undergraduate Students
Prior Assembly Experience	2 participants

A power analysis showed that the sample size of 13 participants was appropriate for this study, with a required power of 0.80. This experiment was designed as a pilot study (levels 1 and 2 of the three-layer I5.0 implementation framework) to understand the manual assembly process from a cognitive ergonomics perspective and to identify variables for future validation studies. For the exploratory eye-tracking studies conducted in controlled laboratory environments, sample sizes in the range of 10–15 participants are well-established in the literature as sufficient to identify primary cognitive load trends, behavioral patterns, and areas of interest for further investigation [56]. The gender distribution (4 females and 9 males) reflects the composition of the volunteer pool drawn from the undergraduate engineering student community at Louisiana Tech University. The participants were volunteer undergraduate students from the college community. Two participants had previous manual assembly experience. All were required to have normal or corrected-to-normal vision and were not colorblind. The participants were assessed in a simulated manual assembly environment. Prior to participating in the study, informed written consent was obtained from each participant. This study was conducted in compliance with the Louisiana Tech University Internal Review Board (HUC-22-034, 11/2021).

3.3. Apparatus and Stimuli

The experiment was held in a light-controlled laboratory room. Among different common manual assembly system configurations, a single-bench workstation was chosen for this experiment, with a seated-worker posture. The workstation was located beside the computer and eye-tracking platform, with the worker directed away from the screen to prevent distractions. This setting was kept for all participants for consistency purposes. The workstation was equipped with an organized toolbox that contained tools and sub-assemblies, measurement and inspection sheets, the eye-tracking calibration target and glasses, and a sheet of assembly instructions. Before the experiment began, each participant was given a briefing on the task, the calibration process, and the time limit.

A Pupil Core wearable eye-tracker from Pupil Labs (Berlin, Germany) was used to record the visual metrics while performing the experiment (Figure 1). The eye-tracker

consisted of a world camera and two eye cameras. The world camera was a 180° adjustable camera with a 60 Hz sampling frequency and a 1280 × 720 pixel resolution. The eye cameras were adjustable in the front/back direction and were capable of recording the user's gaze point, pupil behavior and blink with 200 Hz sampling frequency and a 192 × 192 pixels resolution. The Pupil Core eye-tracker was chosen as it showed suitable features for manual assembly tasks. The eye-tracker was made from PA12 Nylon, which is very lightweight and can be worn over safety glasses, greatly reducing interference during manual assembly dynamic tasks. The eye-tracker was connected to a Dell computer with a Windows 10 operating system via USB. It was run with the Pupil Capture v3.4.0 desktop app, which enables data capture, recording, and a real-time data relay.

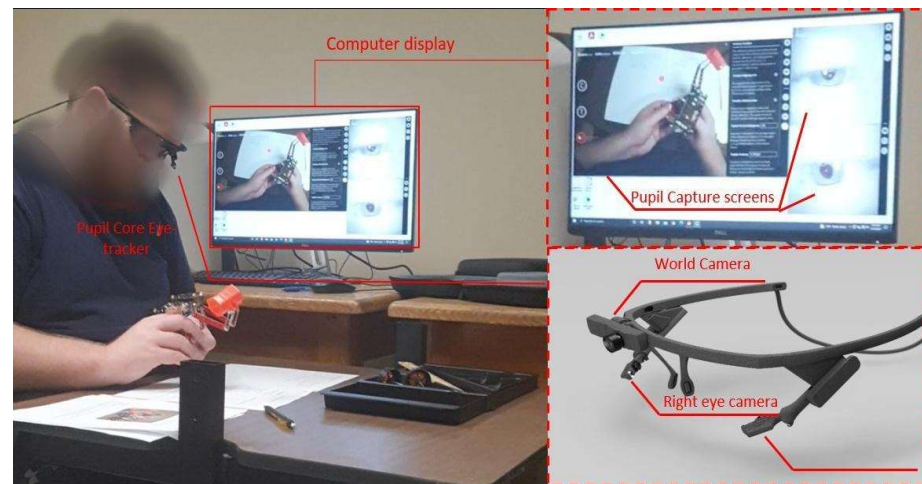


Figure 1. (Left) Experimental apparatus. (Right) Pupil Capture desktop app's real-time display of the experiment, captured by the eye-tracker cameras; Pupil Core eye-tracker.

3.4. Procedure

A manual assembly experiment was designed using a toy excavation vehicle (Aole Gainan Co., Ltd., Amazon, Seattle, WA, USA). The experimental procedure is summarized in Figure 2. After obtaining consent, participants were seated at the workstation and answered a pre-questionnaire. The eye-tracking was then calibrated, and then the assembly and inspection tasks were performed, followed by a post-questionnaire.

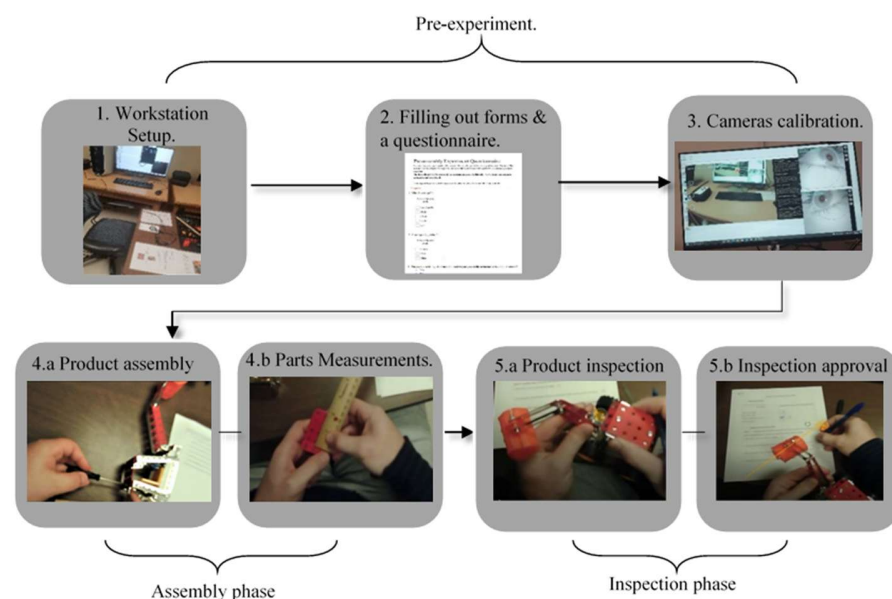


Figure 2. Experimental procedure overview.

The world camera was adjusted in a rotational (up and down) movement to best capture the assembly work angle in front of the participant, and was calibrated to obtain the best recording clarity. The glasses were calibrated using a five-point calibration on-screen method for each participant using a 3D eye model. The eye cameras were adjusted for each participant in a back-and-forth movement to obtain the best pupil capture during the dynamic assembly process. Immediately following the calibration process, the manual assembly task took place.

3.4.1. Assembly Phase

Assembly instructions were provided on a sheet in a step-by-step manner. The first page of the instructions sheet showed a picture of the final product that participants could refer to at any point. In addition, the assembly instructions sheet included a description of the provided parts, tools, and subassemblies. Figure 3 shows the workstation configuration and workbench layout for these phases.

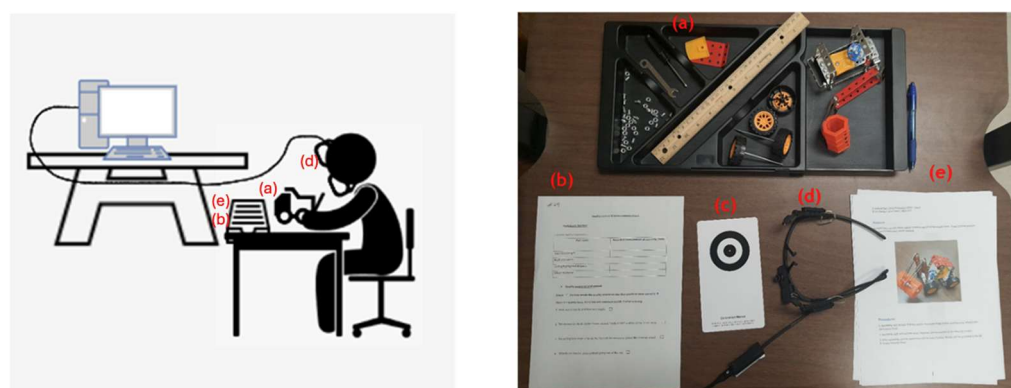


Figure 3. (Left) Single-work station configuration with a seated worker performing manual assembly while wearing the eye-tracker. (Right) The workbench layout with (a) toolbox, (b) measurements and inspection sheet, (c) the calibration target, (d) eye-tracking glasses, and (e) assembly instructions. Each element that corresponds to the part shown in the left and right images are labeled accordingly.

3.4.2. Inspection Phase

The inspection phase of the experiment directly followed the assembly phase. Participants were required to inspect the finished product for four critical subassemblies. Inspection requirements were provided on the Measurements and Inspection Sheet. Participants were asked to inspect four critical parts of their assembled product and write their judgment on the inspection sheet. The critical parts were chosen based on their importance in relation to the final product's function. Table 2 shows the product inspection criteria.

Table 2. Product inspection criteria.

Inspected Part	Inspection Criteria
Seating area	Sturdiness and alignment
Loader head	Sturdiness and rotation angle flexibility
Ceiling	Sturdiness and direction
Wheels	Sturdiness and motion

3.5. Variables

The variables analyzed were organized in two categories: cognitive load and human performance. Measures of cognitive load included fixation duration (ms) and fixation count (fixations/ms), with higher numbers indicating a higher workload [8,55]. Human performance variables included transitions (between AOIs) and the number of errors. Each

experimental run included two types of assembly tasks: (1) attaching and (2) measuring parts. The difference between the average fixation duration of measurements and attaching assembly tasks was calculated as a percentage for each participant to normalize the data. The study variables are shown in Table 3.

Table 3. Eye-tracking metrics and associated definitions.

Eye-Tracking Metric	Definition
Total fixation duration (ms)	Total time each participant fixated on each AOI
Average fixation duration (ms)	Average duration of fixations within each AOI
Total fixation count	Number of fixations within each AOI
Transition count	Number of transitions between AOI's
Within-subject variation percent in fixation duration	Difference between a measurement fixation duration and attachment fixation duration for the same participant (%)

Based on the prior literature indicating that tasks requiring higher cognitive processing produce longer fixation durations and higher fixation counts [8,55], measurement tasks, which require knowledge-based processing according to Rasmussen's SRK framework [57], were expected to produce elevated eye-tracking metrics relative to attachment tasks, which are more skill-based in nature. Similarly, tasks involving geometrically complex parts were expected to be associated with higher error rates [58,59].

For comparison purposes, the within-subject variation percentage in fixation duration was calculated using the equation below. This shows the proportional change for an individual between the two types of tasks, controlling for individual differences and enabling fair comparisons.

$$\frac{\text{Measurement fixation duration} - \text{Attaching part fixation duration}}{\text{Measurement fixation duration}} \times 100 (\%) \quad (1)$$

A transition is defined as two subsequent fixations falling into different AOIs. Participants are predicted to follow a standard path to complete the assembly process. The transitions measured with eye-tracking are used to show the actual path that the assembler followed in both the assembly and inspection phases, and how this differed from the predicted path.

3.6. Data Analysis

During the experiment, the assembly process videos and eye movements of the participants were recorded by the eye-tracker in real-time. Each participant's recording was analyzed individually and annotated using the dynamic AOI feature. Dynamic AOIs were established for the two phases of the manual assembly task (the assembly phase and the inspection phase). Each geometrical shape highlights the parts of the assembly process that we are interested in, and each AOI dimensions continuously adjust according to the assembly object's shape to increase data accuracy.

The task included nine pre-set dynamic AOI's for the assembly phase and four pre-set dynamic AOIs for the inspection phase. Manual assembly phases and the corresponding dynamic AOIs are shown in Table 4.

Table 4. Manual assembly phases and corresponding AOI abbreviations.

Phase	AOI Annotation	Description
Common to both phases	AS PP	Assembly Sheet Product Picture
Assembly Phase	Measure BS L&W Attach BS Attach LH Measure CE Attach CE Measure DIA Attach WH	Measure Backseat Length and Width Attach Backseat Attach Loader Head Measure the Ceiling Attach Ceiling Measure Wheel Diameter Attach Wheels
Inspection Phase	Inspect BS Inspect LH Inspect CE Inspect WH	Inspect Backseat Inspect Loader Head Inspect Ceiling Inspect Wheels

4. Results

4.1. Assembly Phase

4.1.1. Cognitive Load

Fixation duration and fixation count were used to evaluate cognitive load. For comparison purposes, AOIs of the assembly phases were split in two categories: attaching parts' AOIs, and measurement AOIs. The average fixation durations and fixation counts across all 13 subjects are summarized in Table 5.

Table 5. Average fixation durations and fixation counts across all 13 subjects.

Task	Average Fixation Duration (ms) $\pm$ Std Dev	Average Fixation Counts $\pm$ Std Dev
Attaching	272 $\pm$ 86.6	217 $\pm$ 73.1
Measuring	294 $\pm$ 99.5	118 $\pm$ 58.4
Inspection	247 $\pm$ 73.6	40 $\pm$ 16.6

Additionally, the average mean per area of interest is summarized in Table 6.

Table 6. Average mean across subjects by AOI.

Metric	AS	BS	LH	PP	CE
Mean Duration (ms) $\pm$ Std Dev	210 $\pm$ 43.6	279 $\pm$ 176.7	283 $\pm$ 90.8	250 $\pm$ 124.8	313 $\pm$ 109.4
Mean Count $\pm$ Std Dev	327 $\pm$ 117.9	244 $\pm$ 152.3	230 $\pm$ 114.1	64 $\pm$ 98.8	300 $\pm$ 106.3
Metric Cont.	WH	MBS	MCE	DIA	
Mean Duration (ms) $\pm$ Std Dev	235 $\pm$ 72.6	276 $\pm$ 100.3	275 $\pm$ 106.5	333 $\pm$ 167.4	
Mean Count $\pm$ Std Dev	137 $\pm$ 92.1	193 $\pm$ 101.8	86 $\pm$ 54.2	76 $\pm$ 55.4	

The distribution of fixation duration and fixation count across AOIs is illustrated in Figures 4–6.

Figure 4 shows the fixation durations (ms) for the participants in each of the attaching parts and measuring AOIs. This information can help identify tasks with higher cognitive load, comparing measuring and attaching tasks. When examining individual participant data, 46% of the participants experienced a higher workload while measuring the wheel diameter. Comparing total average fixation durations between the two types of tasks, measuring parts was 9% higher than attaching parts.

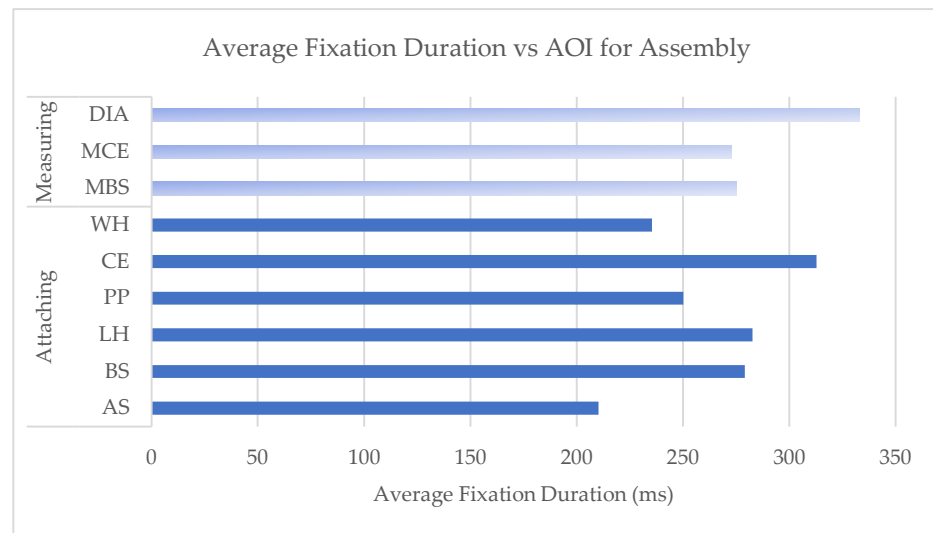


Figure 4. Average fixation duration of all participants for the measuring and attaching subtasks.

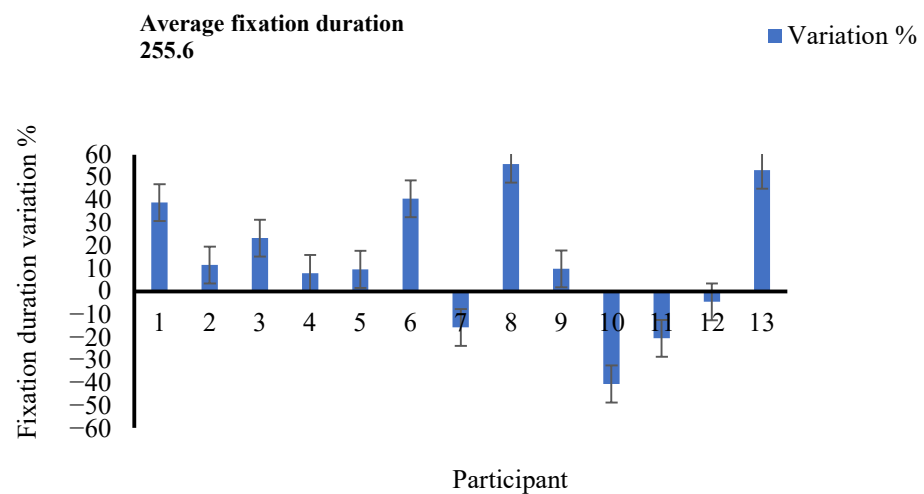


Figure 5. The variation percent between fixations of attaching assembly parts and measuring assembly parts.

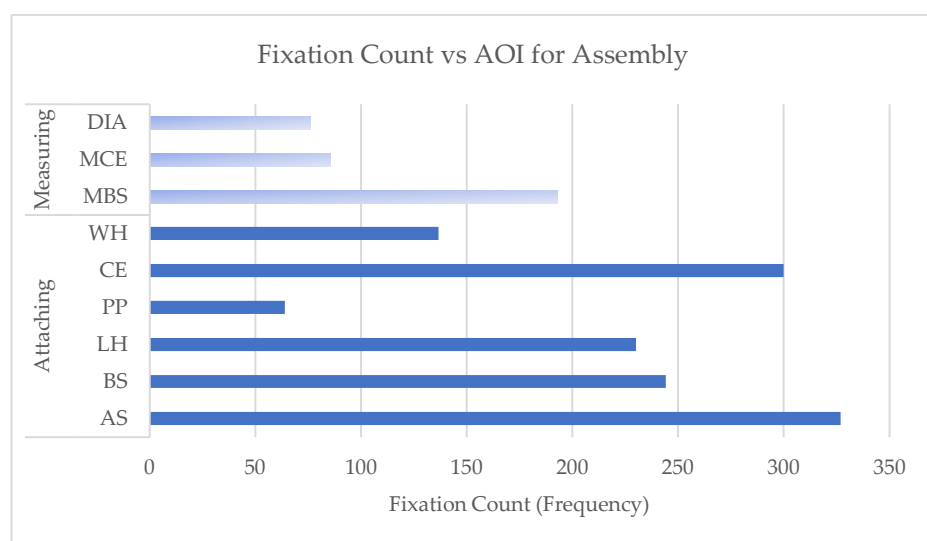


Figure 6. Average fixation count of all participants for the measuring and attaching subtasks.

Figure 5 shows the variation in percentage between fixations when attaching assembly parts and measuring the assembly parts. The results showed that 69% of the participants showed an increase in fixation durations when performing measurement requirements; when attaching assembly parts, they showed a peak increase of 56%. On the other hand, the remaining participants showed a decrease in fixation durations when performing measurements.

The highest fixation count was associated with using the assembly sheet to attach parts, which indicates the participants were using the provided reference.

To determine whether the observed differences in cognitive workload across tasks were statistically significant, a paired *t*-test was conducted on the eye-tracking metrics. There was no statistically significant difference in the fixation percentage. The analysis revealed a statistically significant difference in the average fixation count between the assembly ($M = 167.6$, $SD = 60.4$) and inspection phases ($M = 40.5$, $SD = 16.6$), $t(12) = 7.64$, $p = 0.000$. Specifically, participants exhibited approximately 49 more fixations during the assembly phase compared to the inspection phase, indicating a higher cognitive demand associated with the physical manipulation and attachment of parts. Furthermore, within the inspection phase, tasks requiring measurement (e.g., measuring wheel diameter) produced significantly longer fixation durations compared to simple visual checks, further supporting the hypothesis that measurement tasks impose a higher cognitive load.

An analysis of visual transition patterns further supports these findings. The predicted assembly path is shown in Figure 7. As illustrated in Figure 8, participants frequently deviated from the predicted standard assembly path. The actual transitions were considerably more random than the ideal sequential path, with participants making numerous back-and-forth transitions between the assembly sheet and part AOIs. This random behavior is consistent with higher cognitive uncertainty and reduced process efficiency. With respect to assembly errors, the highest error probability was associated with parts sensitive to geometry, which also exhibited the highest fixation count. This relationship between high-workload AOIs and high-error AOIs supports the use of eye-tracking metrics as a predictor of assembly error risk. These findings are consistent with prior work establishing that categorizing human error by geometry-sensitivity can help to predict the highest error occurrence probability [58].

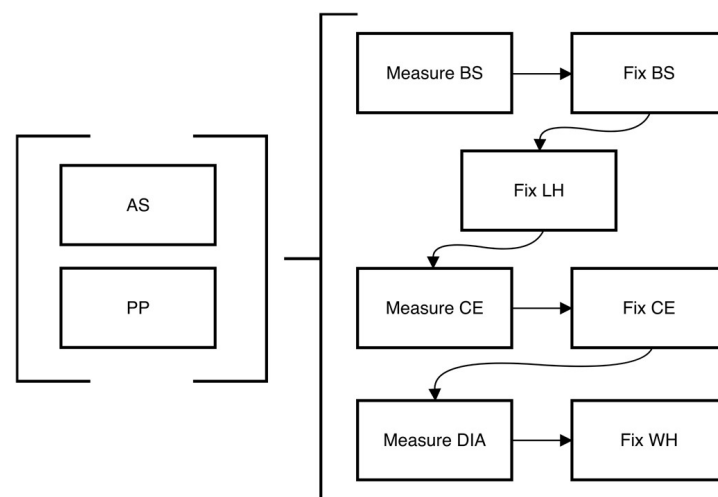


Figure 7. Standard predicted transition path in assembly task. Arrows indicate flow between parts. Table 4 presents the abbreviations.

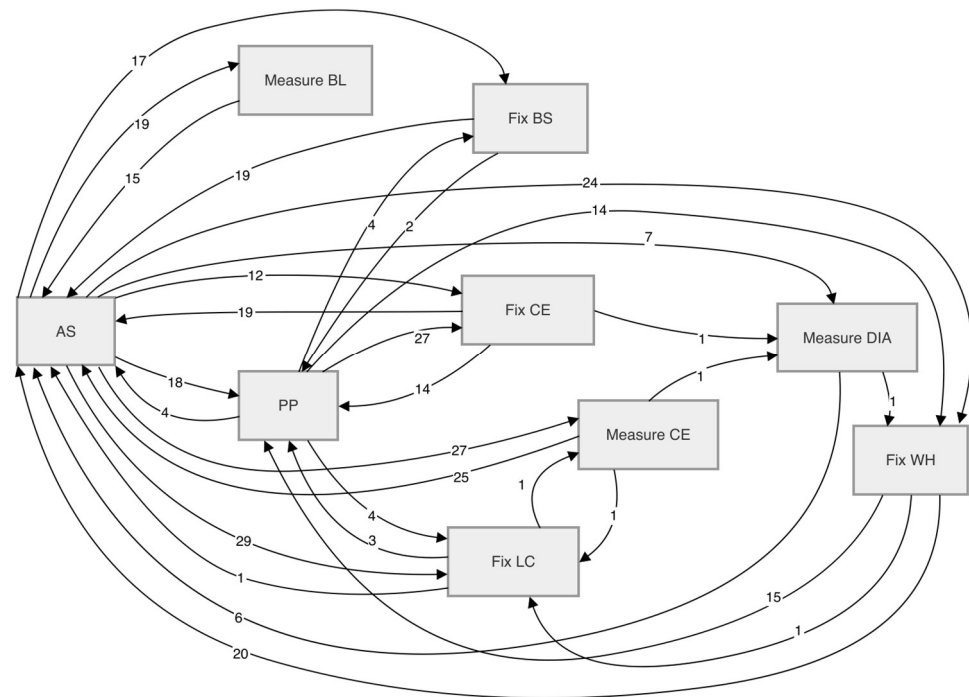


Figure 8. Actual transitions between AOIs, provided by gaze data. Table 4 presents the abbreviations. Arrows indicate flow between parts.

4.1.2. Human Performance

Human performance was analyzed by the transition count provided by the transition matrices, as well as the number of errors observed in the process. Figure 7 shows the standard predicted path that the participants were expected to follow during the process. By analyzing eye-tracking transition matrices data, the results show a variation in actual transitions from the standard path.

Figure 8 shows the actual path followed by participants during assembly. The rectangles represent the assembly AOIs in the order required by the assembly instructions sheet. Arrows represent the direction from one AOI to another that was followed by participants. The numbers on arrows represent the total number of actual transitions followed by all participants for that path. For example, participants transitioned from the “Assembly Sheet” AOI to “Measure the Ceiling” AOI a total of 27 times.

The second measure of human performance is the number of assembly errors. The main goal was to detect process errors by analyzing eye-tracking data and observing process recordings carefully. Manual assembly errors in this study were categorized based on task observation through eye-tracking recordings. Table 7 shows the assembly phase error categories and descriptions.

Errors in the assembly phase were observed by analyzing each participant’s task video recordings. Afterwards, errors were classified into during-assembly errors (67%) and finished product errors (33%). During-assembly errors represent the errors caused by the assembler and lead to final product errors.

Assembly-phase errors were higher during assembly and decreased as the participant finished the final product. Loose attachments in the final assembled errors represented 24% of the overall total errors (during-assembly + finished product errors) and 85% of the final product errors.

Table 7. Assembly phase process errors.

Label	Description
Errors During Assembly (Leading to Errors in the Finished Product)	
1. Interpreting requirements	Misinterpreting requirements in assembly steps
2. Step order	Doing assembly steps in reverse when order is required and/or starting inspection instead of assembly
3. Direction/Alignment	Errors related to the wrong direction of a part or incorrect alignment of parts
4. Not using tools properly	Not using tools when they are required to perform the task correctly
5. Spatial (limited access)	Errors related to points in assembly work that is hard to access using hands and tools
6. Dimensions (size/similarity)	Errors related to using the wrong part or wrong dimension during assembly
Finished Product Errors	
1. Dimensions (size/similarity)	Wrong assembly of parts due to the size or similarity of parts or subassemblies
2. Direction/Alignment	Parts assembled in the wrong direction or aligned improperly with other parts/subassemblies
3. Loose attachments	Final product having loose connections between parts or subassemblies

4.2. Inspection Phase

The inspection phase required the participants to make sure that the product looks like the final product picture, functions properly, and meets the requirements described in the inspection sheet.

4.2.1. Cognitive Load

For the inspection process, cognitive load was measured by average fixation durations (ms) and normalized fixation count.

The results showed that 53% of the assemblers had a higher cognitive load (a longer fixation duration and higher fixation count) while inspecting the loader head and the backseat together compared to the other two inspected parts (ceiling and wheels), shown in Figure 9.

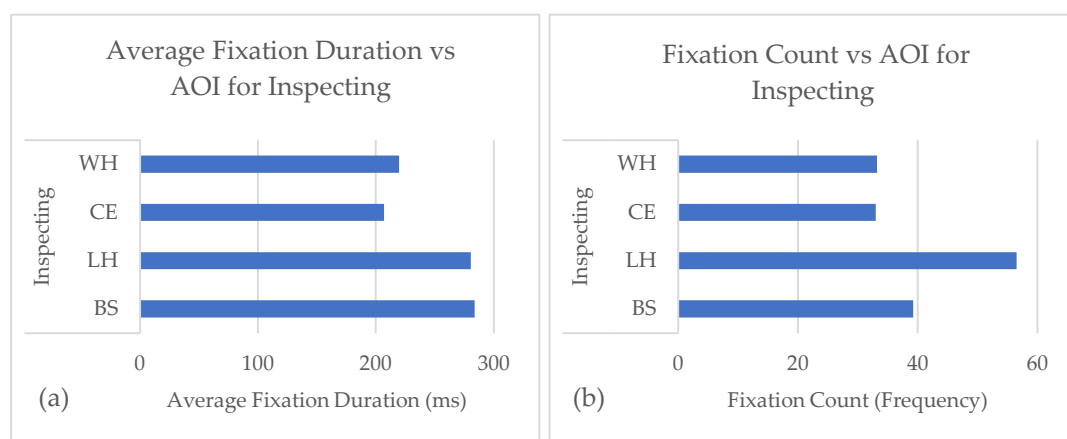


Figure 9. Average fixation duration (a) and fixation count (b) for all participants for each of the AOIs used for inspection tasks.

To examine the relationship between cognitive demand and inspection performance, a Pearson correlation was conducted between average fixation duration and the number of inspection errors across all 13 participants. The analysis revealed a strong negative correlation, $r(11) = -0.710$, $p = 0.006$, 95% CI $[-0.907, -0.262]$, indicating that participants who exhibited longer average fixation durations during the inspection phase committed

fewer inspection errors. This suggests that greater visual engagement with the inspected parts, reflecting more thorough cognitive processing, was associated with improved inspection accuracy.

4.2.2. Human Performance

Human performance was analyzed for the inspection phase. Transitions in the inspection phase and the number of errors were used as measures of human performance.

In the actual inspection procedure, participants were expected to follow the standard predicted inspection path (Figure 10): Inspect Backseat → Inspect Loaderhead → Inspect Ceiling → Inspect Wheels. However, not all participants adhered to this sequence. Figure 11 illustrates the actual inspection paths observed. Boxes shaded in white represent the four AOIs that constitute the standard inspection path, while gray-shaded boxes represent non-standard AOIs, presented as deviations from the expected sequence (Attach Backseat, Refer to Product Picture, and Measure Wheel Diameter). Straight arrows indicate transitions along the standard path, and curved arrows indicate deviations. The number on each arrow represents the number of participants who followed that transition. Of the 13 participants, 9 followed the first standard transition (Backseat → Loaderhead), and 11 followed each of the subsequent two standard transitions (Loaderhead → Ceiling and Ceiling → Wheels). Notably, two participants returned from Inspect Wheels all the way back to Inspect Backseat, indicating re-inspection behavior. Table 8 below summarizes the standard path transitions and the number of participants who followed each, compared to those who deviated.

Human performance was also measured by the number of inspection errors. An inspection error was defined as the approval of a part when it should not be approved. Table 9 shows inspection error types.

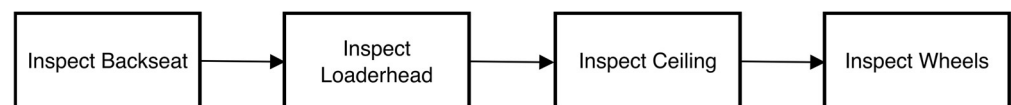


Figure 10. Standard predicted inspection path.

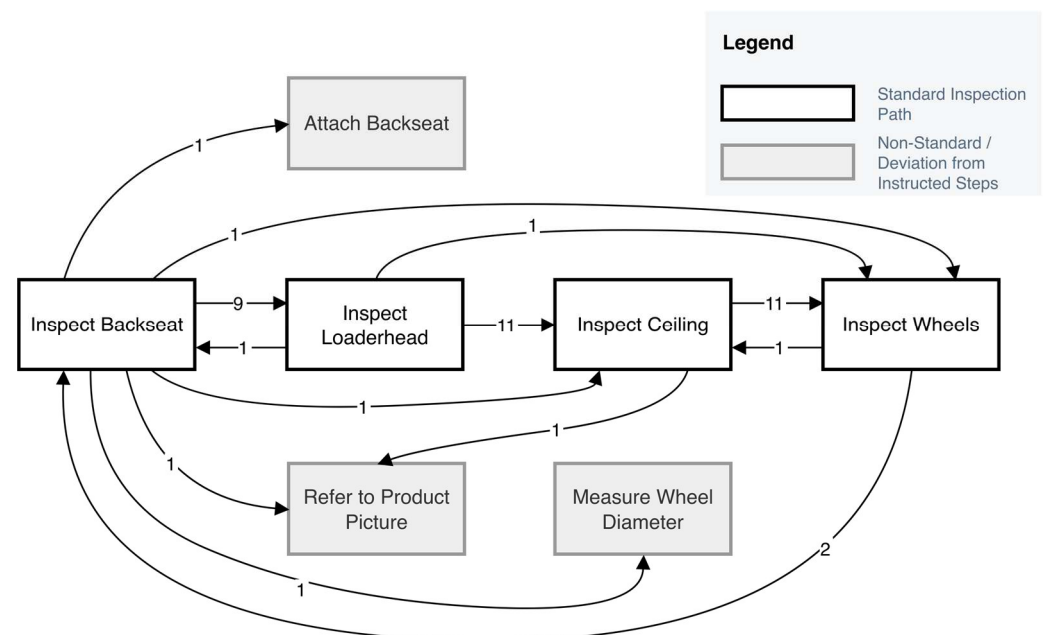


Figure 11. Actual inspection path. Bold boxes and arrows represent the standard predicted path; amber boxes and arrows represent non-standard deviations. Numbers on arrows indicate the number of participants who followed that transition.

Table 8. Summary of inspection path transitions: standard path vs. non-standard deviations. Numbers represent participants, with a total of 13.

Transition	Type	Number If Participants Followed	Notes
Inspect Backseat → Inspect Loader head	Standard	9	4 deviated or took non-standard route first
Inspect Loader head → Inspect Ceiling	Standard	11	2 visited Refer to Product Picture first
Inspect Ceiling → Inspect Wheels	Standard	11	1 visited Refer to Product Picture first
Attach Backseat → Inspect Backseat	Non-Standard	1	Participant entered inspection from assembly AOI
Attach Backseat → Inspect Wheels	Non-Standard	1	Skipped directly to the end of the standard path

Table 9. Inspection error types and sources.

Description	Definition	% of Total Errors
Approved a loose attachment	When the participant did not record a loose screw/nut attachment in the inspection sheet	56%
Approved wrong inspection technique	When the participant approved an assembly in the wrong direction	22%
Approved a missing part	When the participant approved a missing part in the inspection sheet	4%
Approved without inspection	When the participant recorded the check in the inspection sheet without inspecting	9%
Approved with incomplete inspection	When the assembler partially inspected the subassembly and recorded a check in the inspection sheet	9%

To examine the role of the assembly sheet at this stage, Figure 12 shows the relationship between the clustering of inspection errors and the total time participants spent referring to the assembly sheet.

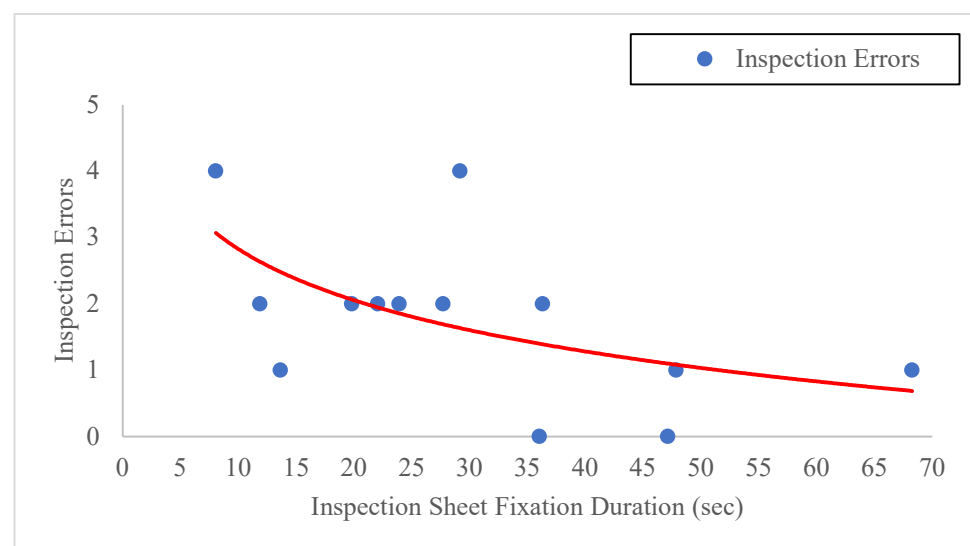


Figure 12. Duration of references to assembly sheet versus number of inspection errors.

This graph shows that when spending at least 37 s on the inspection sheet the errors that occurred were one or fewer for the participants.

5. Discussion

The data were analyzed looking at human performance metrics and cognitive workload. Transition information and errors were used to analyze human performance, while the eye-tracking measures of fixation duration and count were used for cognitive workload indicators.

The frequency of transitions indicates whether the worker is following the set of predicted viewing paths that would align with an efficient process. The results here showed a random behavior from some of the assemblers rather than the expected standard behavior assumed in ideal case scenarios. During the assembly process, many of the participants deviated from the predicted path, resulting in loss of efficiency with increased transitions, while often neglecting to spend the time required in reviewing the instruction sheet for sound performance. The highest number of transitions was observed along the standard path during the inspection phase, which means that, most of the time, a participant would inspect the product as expected. However, there were a few transitions in the opposite direction, going back to a previous AOI. This may indicate uncertainty from the operator as well as the possibility of error. For example, there were two backward transitions after finishing the inspection process for the first inspected part (the backseat). Given the speed–accuracy tradeoff inherent in inspection tasks, these findings suggest that operator assistance should be provided at the end of each inspection stage, providing feedback on performance and process progress to support situation awareness. Understanding transitions can help when providing feedback about the inspection behavior of an assembler and how efficiency can be improved while lowering cognitive workload.

More inspection errors were observed when assemblers spent less than 30 s referring to the inspection sheet. As the inspection sheet consisted of detailed descriptions of the required inspection, longer durations helped reduce inspection errors. This is in alignment with the cognitive bias research [58–61], as cognitive biases and associated errors are more prevalent when the operator makes quicker decisions.

The results showed that 69% of the participants showed an increase in fixation durations while performing measurements versus attaching assembly parts, with the highest increase being 56%. These results are used as a predictor of cognitive load related to assembly tasks that require attaching parts and handling skills versus assembly tasks that require measurement skills. This indicates that assistance should be built into the system when measurement is required. According to Rasmussen's Skill, Rule, and Knowledge-based framework, the assistance should be provided in such a way that it alleviates load by translating the highly cognitive, knowledge-based task to a skill- or rule-based task for the operator [57].

According to [58], categorizing human error can be used to predict the highest error occurrence probability. For example, the results show that the highest error probability was associated with assembly, where the geometry of the parts impacted their placement, which agrees with the findings of Torres et al. [56]. This indicates that the worker may benefit from assistance when assembling this type of part. In the inspection phase, 56% of the total inspection errors were due to approving loose attachments and 22% were due to using the wrong inspection technique. With such a high percentage of errors being due to approving a process that was not performed correctly, decision support should focus on providing additional input to the worker. While workload results are mixed, a greater number of participants showed increased cognitive load during the inspection phases, with errors occurring in both phases. In accordance with Reason's [62] Swiss Cheese model, this shows how a faulty item can be produced with the latent errors lining up across both the assembly and inspection phase, so support to mitigate cognitive load and assist the operator across phases, especially early on in the process, is important to incorporate into an I5.0 system.

While designed as an exploratory study to define when and how cognitive assistance can be built into a manual assembly and inspection process, following Mark et al.'s [7] framework, there are limitations to the findings. While designed to capture a number of different types of assembly and inspection tasks, the experiment could only capture a limited number of these tasks. In addition, the results were based on novice workers, and

adjustments may need to be made in situations where workers are more experienced. Therefore, the results are useful for the increasingly widespread mass-customization assembly process, where differences in the assembly of different parts are common.

6. Conclusions

This study applied levels 1 and 2 of Mark et al.'s I4.0/I5.0 implementation framework to identify cognitive load patterns in manual assembly and inspection tasks using eye-tracking [7]. Three task categories emerged as priority targets for cognitive assistance: measurement tasks (elevated workload in 69% of participants), the inspection of geometrically complex parts (elevated workload in 53%), and quality control verification (56% of inspection errors were due to approving loose attachments). Transition analysis further showed that workers who spent fewer than 37 s reviewing the assembly sheet made more errors, underscoring the value of assistance systems that support adequate reference consultation rather than solely optimizing speed. The backward transitions observed during the inspection phases indicate uncertainty and potential error occurrence, suggesting opportunities for real-time feedback systems that provide confirmation or alerts when operators deviate from expected patterns. In conclusion, the results of this study not only identified opportunities for integration, but also demonstrated the feasibility of eye-tracking as an integral part of the human–computer system in the assembly environment. Considering the importance of cost control in the manufacturing industry, the reasonable commercial price of many eye-trackers (like the Pupil Core used here, which is approximately 4000 USD) allows them to be integrated and used in the manufacturing environment while ensuring the reliability of the process. Although the study was limited to novice workers and a constrained task set, these conditions reflect the mass-customization contexts, characterized by novel and infrequent task variation, to which the findings are most applicable. In addition, the methodology established in this study provides a template for Level 3 implementation in Mark et al.'s [7] framework, transitioning from pilot projects to the operational deployment of cognitive assistance systems in industrial settings.

Future work should advance to Level 3 implementation by deploying and validating targeted cognitive assistance interventions in operational settings, and may benefit from integrating additional physiological measures and machine learning to enable real-time cognitive state monitoring and error prediction.

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