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Identifying Assembly Operations Suitable for Augmented Reality Support: A Human Capability-Based Framework

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Abstract:

Manufacturing companies increasingly face shortages of skilled workers, creating a need for technologies that enable unskilled operators to perform complex assembly tasks while maintaining acceptable performance and quality levels. This study proposes a capability-oriented framework for evaluating where Augmented Reality (AR) can effectively support industrial assembly. The framework first identifies the human capabilities required by assembly tasks and links them to performance-, quality-, and wellbeing-related key performance indicators. These measures are then used to classify tasks according to their cognitive demand and operational difficulty.

The framework was evaluated through a benchmark study of electrical-panel assembly, comparing AR-assisted unskilled operators with expert operators using conventional paper-based instructions. The results show that AR effectiveness depend on the requirements of each task. AR-assisted operators progressively reduced their understanding-time gap across comparable component-positioning tasks and committed fewer positioning errors than the expert group. During the wiring tasks, AR-assisted unskilled operators achieved understanding and execution times comparable to, or shorter than, those of the expert benchmark. However, AR provided more limited support when task performance depended primarily on manual dexterity and practical experience. It also offered limited added value for simple tasks, where interacting with detailed digital instructions could increase cognitive demand. Participants also reported manageable workload and positive system usability. Future research should validate the framework, indicators, and classification thresholds across different assembly processes and training scenarios.

Keywords: Augmented Reality; Industrial Assembly; Unskilled Operators; Human Capabilities; Benchmark Study.

1. Introduction

Manufacturing companies increasingly face labour shortages, particularly in the skilled technical occupations required for industrial assembly [1, 2]. Electricians are among the most difficult professional profiles to recruit, despite their essential role in assembly and wiring operations. These shortages can limit production capacity and increase dependence on a small number of experienced workers [1, 3]. Growing product variety and frequent changes in assembly requirements further increase training needs and reduce opportunities to learn through repetition [4, 5]. Companies therefore need solutions that accelerate training, reduce errors, and improve production flexibility without compromising quality or safety. One possible strategy is to involve population groups that are traditionally underrepresented or vulnerable in employment contexts. According to the European Commission and Cedefop [2, 6], adults with low qualification or skill levels are at greater risk of labour market exclusion and represent an important target for upskilling initiatives. In industrial environments, these individuals can be regarded as unskilled operators, namely workers who lack the experience or vocational competencies required to perform complex manufacturing tasks independently. Supporting their integration could help address workforce shortages while contributing to more inclusive manufacturing systems. Augmented Reality (AR) represents a promising technology for this purpose. By overlaying task-relevant information onto the physical workspace, AR can provide contextual instructions, guide operators' attention, and support accurate task execution [4, 7, 8]. Previous studies have reported improvements in assembly performance, learning outcomes, and operator confidence compared with conventional instructions [4, 7, 8]. AR has also shown potential for onboarding operators with limited experience and supporting progressive learning [5, 7]. Despite these benefits, AR remains insufficiently adopted in industry. Its implementation requires investment in hardware, software, content preparation, maintenance, and training, while its economic benefits are difficult to estimate in advance [9]. Head-mounted displays may also cause physical discomfort, visual fatigue, and additional cognitive demands during extended use [4, 7–9]. Continuous use throughout an entire work shift may therefore be neither practical nor beneficial. AR assistance should instead target tasks for which contextual guidance can provide sufficient value to justify its costs and effects on operators.

However, the availability of AR technology does not indicate where its implementation is appropriate. Its effectiveness depends on task complexity, the capabilities required from the operator, and the information provided. Detailed guidance may benefit complex or information-intensive activities but offer limited value or introduce unnecessary interaction demands in simple operations. Although investment models support the economic evaluation of AR-based training [9], companies still lack a structured task-level approach for selecting suitable assembly operations. This is particularly problematic for small and medium-sized enterprises, which must prioritize limited resources. Selecting unsuitable tasks may result in implementation and maintenance costs that exceed the benefits obtained. This decision problem is evident in electrical-panel assembly, which relies on experienced electricians and requires operators to identify components, interpret technical documentation and electrical schematics, and perform precise positioning and wiring operations. For unskilled operators, these requirements create cognitive and operational difficulties. However, the support required varies across the process: some operations mainly involve component identification and positioning, whereas others depend on technical understanding, wiring experience, and manual execution. Determining where AR is useful therefore requires examining its contribution at the level of individual operations. Previous research has demonstrated the benefits of AR for industrial assembly and training, but limited

attention has been given to comparing the task-level performance of AR-assisted unskilled operators with an appropriate reference condition. Existing studies mainly report aggregate improvements in time, errors, or workload without explaining how these outcomes relate to the capabilities required by different tasks. Consequently, it remains unclear how companies should combine performance indicators, task characteristics, and operator capabilities to determine where AR guidance is useful and where other interventions may be more appropriate.

To address these gaps, this paper proposes a capability-oriented framework for evaluating AR support in industrial assembly. Conceptually, it links the human capabilities required by assembly tasks to performance-, quality-, and wellbeing-related KPIs. Methodologically, it introduces a task-level classification based on cognitive demand and operational difficulty. Empirically, it is applied through a benchmark study comparing AR-assisted unskilled operators with experts using conventional paper-based instructions. The results are interpreted according to each task's capability profile to identify the conditions under which AR provides effective support.

Accordingly, this paper addresses the following research questions:

RQ1: How does the task-level performance of AR-assisted unskilled operators compare with an expert paper-based benchmark?

RQ2: Which task capability profiles characterize operations in which AR-assisted unskilled operators meet or fall short of the expert benchmark?

The remainder of this article is structured as follows. Section 2 presents the related works identified in the literature. Section 3 introduces the proposed research methodology. Section 4 presents the application of the methodology and the main results. Finally, Section 5 discusses the findings, practical implications, limitations, and directions for future research.

2. Related works

Augmented Reality has received increasing attention as a support tool for industrial training and assistance [10–13]. By presenting task relevant digital information directly within the workspace, AR reduces the need to consult separate technical documents and transfer their content to the physical task [11, 14]. This is particularly valuable in environments characterized by complex procedures, product variability, and strict precision requirements [10, 14]. However, AR effectiveness depends on task characteristics, especially complexity. Previous studies report positive but variable outcomes, with limited evidence from real industrial settings [14]. AR appears more effective for difficult assembly tasks, whereas simple operations may receive limited benefits or experience higher mental workload [15–17]. The complexity of AR visualizations should therefore be adapted to the difficulty of the operation [18]. Overall, AR has clear potential for complex industrial assembly but may provide little benefit or introduce additional workload for simple tasks [14–18]. AR may be particularly relevant for unskilled or inexperienced workers who have not yet acquired task specific knowledge through training and practice [19–21]. These operators must interpret unfamiliar technical information and apply it correctly during task execution. Studies involving mechanical, electrical, railway, piping, and naval assembly report that AR can reduce completion time and errors and support users without prior domain experience [19, 20, 22, 23]. These findings indicate that AR can reduce some performance limitations associated with insufficient experience. However, they mainly describe overall performance improvements without explaining which human capabilities are supported or compensated for by AR. Despite these findings, a framework defining criteria for successful AR deployment is still

missing. Existing studies show that AR effectiveness depends on the interaction between task characteristics and the assistance provided, but this relationship remains only partially explored. Radkowski et al. [18] showed that different visual features influence completion time and error rates according to task complexity, indicating that the same guidance may not be appropriate for all operations. Similarly, Wiedenmaier et al. [16] found that AR becomes more advantageous as task difficulty increases. However, these studies do not provide a general model linking AR features, task requirements, worker capabilities, and performance.

The literature therefore highlights a gap in the evaluation of AR for industrial assembly, particularly for unskilled operators. Most studies assess completion time, accuracy, workload, or learning at the overall process level, with limited attention to individual tasks and their capability requirements. Moreover, there is no consolidated framework linking these capabilities to suitable performance, quality, and wellbeing KPIs, nor appropriate benchmarks for assessing whether AR assisted unskilled operators reach acceptable performance. Evidence from structured task level evaluations in realistic industrial settings also remains limited. Consequently, it is still unclear how AR effectiveness should be measured systematically, which task and capability profiles can be supported despite limited experience and education, and when technical knowledge, practical training, or simpler assistance remain necessary.

3. Materials and methods

3.1. Research Methodology

Figure 1 presents the research methodology adopted in this study. The methodology begins with the development of the AR-Supported Capability Assessment Framework, which integrates the analysis of assembly-task requirements with the identification of the human capabilities relevant to task execution and potentially supportable through AR. The framework is developed in Section 3.2 and summarized in Table 2. These capabilities are then linked to the KPIs used to assess AR support. The selected measures include literature-based KPIs, consolidated measures, and newly developed reference-based metrics covering performance-, quality-, and well-being-related results. The KPIs are subsequently applied at the task level to assess cognitive demand and operational difficulty. Based on the resulting values, each operator-task observation is classified as *Standard*, *Cognitively Demanding, Operationally Demanding*, or *Critical*.

The proposed framework is validated through a benchmark study involving an electrical panel assembly case. The task-level performance of AR-assisted unskilled operators is compared with that of experts using paper-based instructions. The results are interpreted according to the capabilities required by each assembly task, allowing the framework to identify the tasks and capability profiles for which AR provides effective support and those for which its contribution remains limited.

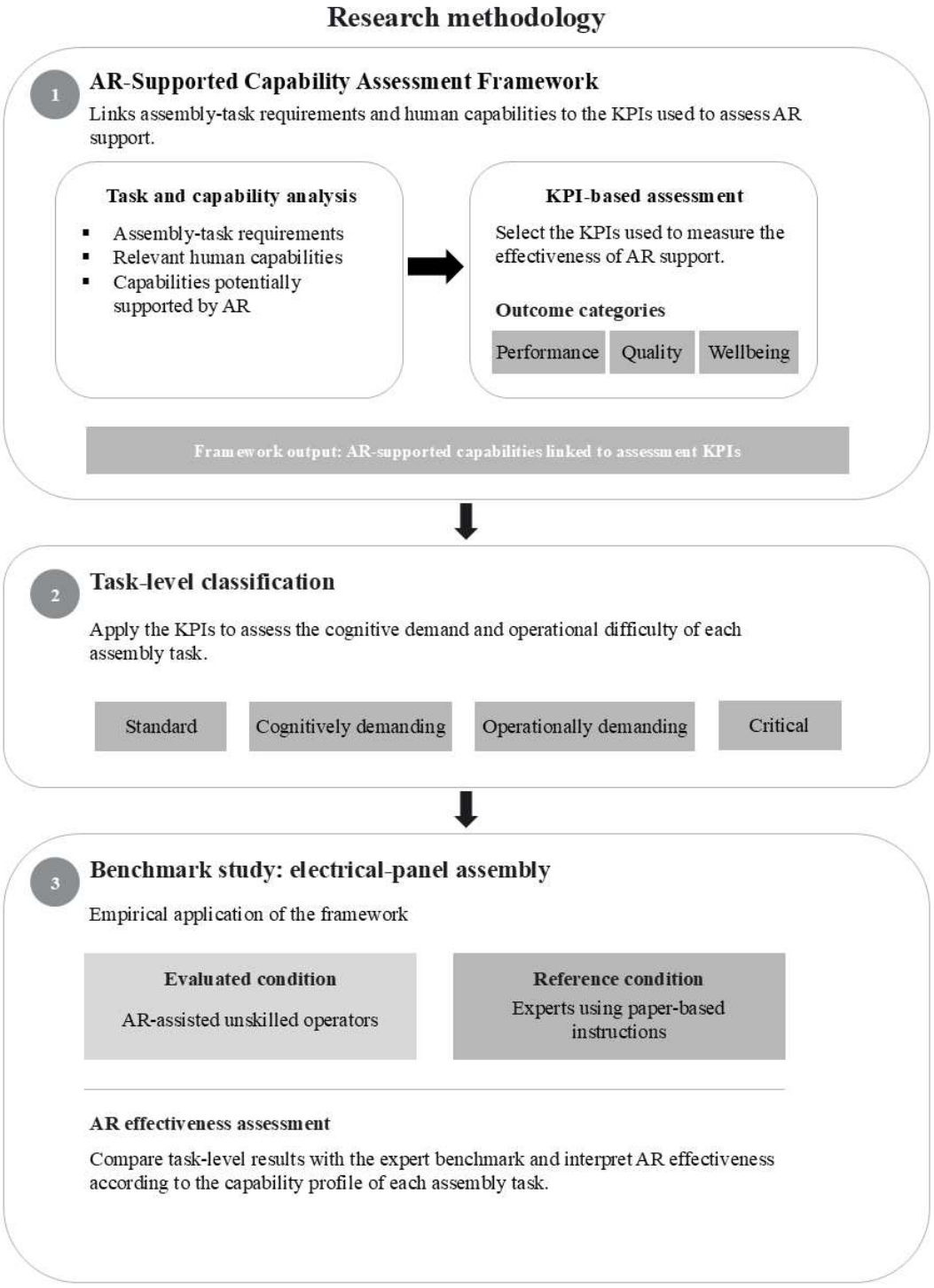


Fig. 1 Research methodology for developing and validating the AR-Supported Capability Assessment Framework

3.2 AR-Supported Capability Assessment Framework

To investigate how AR can support unskilled operators in manual assembly, a capability matrix was developed. It identifies the worker capabilities that are both relevant to assembly tasks and potentially supported by AR-based training and assistance. The initial capabilities were drawn from Fleishman's taxonomy [24] and the occupational framework proposed by Mark et al. [25]. Since these frameworks cover a broad range of capabilities, a two-stage filtering procedure was applied. The first stage evaluated whether each capability could be supported by AR. The second assessed its relevance to industrial assembly. The inclusion and exclusion criteria are summarized in Table 1.

Table 1 Inclusion and exclusion criteria applied during the capability filtering procedure

Filtering Stage	Decision	Criterion
Stage 1: Potential for AR support	Include	Cognitive support: capabilities that can benefit from the presentation, organization, or contextualization of information.
	Include	Procedural and decision-making support: capabilities that can benefit from real-time guidance supporting correct execution, error reduction, and operational efficiency.
	Include	Attentional support: capabilities that can benefit from highlighting relevant information, directing visual attention, or clarifying spatial cues.
	Exclude	Physical and biomechanical capabilities requiring physical or mechanical intervention rather than informational support.
	Exclude	Physical coordination and balance capabilities, because they cannot be directly enhanced through informational AR support. Manual Dexterity and Reaction Time (Responsiveness) were retained as exceptions because of their relevance to industrial assembly.
	Exclude	Primary sensory capabilities, which are prerequisites for interacting with AR but are not directly enhanced by it.
Stage 2: Relevance to industrial assembly	Include	Capabilities required to understand, interpret, retain, or learn assembly instructions.
	Include	Capabilities involved in positioning, orienting, or manipulating assembly components and tools.
	Include	Capabilities that influence assembly accuracy, efficiency, quality, or completion time.
	Exclude	Higher-level cognitive capabilities extending beyond the predominantly procedural demands of industrial assembly tasks.
	Exclude	Capabilities that cannot be directly supported through AR-based assembly guidance.

The capability-identification process resulted in a final set of capabilities considered relevant to industrial assembly and potentially supportable, directly or indirectly, through AR. The capabilities were derived from established classifications and definitions in the literature [24-26] and complemented by constructs identified as relevant to the industrial assembly context. To support their interpretation within the proposed AR-Supported Capability Assessment Framework, they were organized into three main categories: cognitive, psychomotor, and performance-related capabilities.

Cognitive capabilities concern how operators perceive, process, learn, and apply task relevant information. *Selective attention* supports concentration on relevant elements, while *time sharing* enables attention to shift between activities or information sources [24–26]. *Perceptual speed* allows operators to rapidly compare objects or patterns and recognize visually similar components [24]. *Deductive reasoning* concerns applying general rules to specific problems,

whereas *information ordering* supports the organization of actions and information into the required sequence [24, 25]. *Memorization* enables operators to remember information and procedures, *learning ability* supports the acquisition of knowledge and skills, and *knowledge retention* enables learned information to be recalled over time [24–26]. *Spatial orientation*, *mental rotation*, and *visualization* support the interpretation of spatial relationships and the mental manipulation of components [24, 27]. Finally, *technical understanding* enables operators to interpret technical information and apply relevant principles to assembly problems [25].

Psychomotor capabilities concern physical task execution. *Manual dexterity* supports the accurate manipulation, positioning, and assembly of objects, while *reaction time*, or responsiveness, enables rapid physical responses to visual, auditory, or other signals [24, 25]. These capabilities depend strongly on coordination and practical experience, which AR can guide but may not fully compensate for.

Performance-related capabilities describe the operator's ability to complete assembly tasks effectively. *Independence* concerns performing tasks without external assistance, *correctness* concerns avoiding execution errors, and *working velocity* concerns completing tasks efficiently while maintaining the required quality [25]. These capabilities indicate whether AR enables unskilled operators to perform closer to the expert benchmark.

Together, these capabilities form the capability component of the AR-Supported Capability Assessment Framework. The framework links each capability to the KPIs used to evaluate whether AR provides effective support during industrial assembly. The subsequent task-level analysis therefore considers not only the performance achieved with AR but also the capability profile associated with each assembly task.

Having identified the relevant capabilities, the literature was reviewed to examine which capabilities are supported by AR and which KPIs have been used to measure the effects of this support.

Learning Ability and *Knowledge Retention* are among the capabilities most consistently supported by AR. Studies comparing AR with conventional instructions show that contextual guidance can improve procedural-knowledge acquisition, reduce errors across repeated assembly cycles, and support the maintenance of performance after assistance is removed [28–30]. Learning effects are generally reflected in progressive changes in accuracy, completion time, and reliance on instructions, while retention is assessed through delayed knowledge tests or task performance after a period without AR support. These findings indicate that *Learning Ability* should be measured through performance changes across repeated trials, whereas *Knowledge Retention* requires delayed assessment of knowledge or performance after support is reduced or removed.

Selective Attention, *Perceptual Speed*, and *Information Ordering* concern how operators identify, process, and organize task-relevant information. AR can support these capabilities by highlighting relevant components and tools, providing visual references within the workspace, and presenting assembly instructions in the required sequence [22, 28, 30, 31]. The literature reports improvements in component and tool selection, visual search, sequence reproduction, and the correct application of procedural tasks. Suitable KPIs therefore include selection and sequence errors, visual-search and instruction-reading time, attention switches, and assembly-sequence quiz accuracy. These measures should be interpreted together because longer interaction with instructions may indicate either inefficient guidance or more careful information processing.

Correctness and *Working Velocity* reflect the quality and efficiency of task execution. Across the reviewed studies, AR generally reduced assembly and sequence errors, although the

magnitude of this improvement varied according to the task and the way errors were classified [20, 22, 29, 30]. Evidence concerning completion time was less consistent: some studies reported faster execution with AR, whereas others found limited improvements or additional time associated with interacting with digital instructions [21, 22, 28–31]. Error counts, rates, and categories therefore provide the main KPIs for *Correctness*, while task or assembly completion time is the principal measure of *Working Velocity*. However, time-based results should always be interpreted together with accuracy, task complexity, interface design, and familiarity with AR, since faster execution does not necessarily correspond to better assembly performance.

Overall, the literature shows that AR can support both assembly training and task execution. The strongest evidence concerns *Learning Ability*, *Correctness*, *Information Ordering*, *Knowledge Retention*, and *Selective Attention*. AR may also support *Perceptual Speed* by facilitating the visual identification and comparison of components, although this capability has rarely been evaluated explicitly. The results for *Working Velocity* are less consistent. Most studies rely on completion time, errors, and accuracy, which provide useful measures of productivity and assembly quality but limited information about cognitive demand, operational difficulty, and reliance on external assistance.

Assembly errors - The number of errors occurring during the assembly process is recorded together with their category and severity. Errors are classified as either **major** (***M)*** or **minor (*m)***. Major errors compromise the intended function, safety, or compliance of the assembled product, or require substantial rework. Minor errors do not prevent the product from functioning as intended but may affect its quality, appearance, or conformity with assembly requirements. To account for severity, each error is assigned a weighting factor: 1.0 for major errors and 0.5 for minor errors [32]. These weights can be adapted to the requirements of the assembly process being evaluated.

Help Requests (HR) - represent the occasions in which an operator requires external assistance to understand the AR instructions before proceeding with the corresponding assembly task.

Understanding Time (T_U) - is defined as the cumulative time an operator spends consulting and interpreting the information or instructions associated with a given assembly task. Since the operator may alternate between consulting the instructions and performing assembly activities, T_U may consist of multiple non-consecutive intervals within the same task.

Execution Time (T_E) - is defined as the cumulative time spent by an operator performing assembly-related activities associated with a given task. This metric includes both the Action Time (T_A), corresponding to the duration of value-adding physical assembly operations, and the Other Time (T_O), which comprises supporting activities required to complete the task, such as searching for components or tools. Since participants could alternate between assembly actions, other supporting activities, and instruction consultation, the measured value may consist of multiple non-consecutive Action Time and Other Time intervals within the same task.

$$T_E = T_A + T_O \quad (1)$$

Total Time (T_T) - is defined as the sum of understanding and execution time.

$$T_T = T_U + T_E \quad (2)$$

Understanding Time Ratio (UTR) – compares the time required by the evaluated operators to understand the instructions for an assembly task with a suitable reference value. For each assembly task ***s***, it is calculated as:

$$UTR_s = \frac{\bar{T}_{U,s}}{\bar{T}_{U,s}^{Ref}} \quad (3)$$

Where $\bar{T}_{U,s}$ is the mean Understanding Time of the operators and $\bar{T}_{U,s}^{Ref}$ is the corresponding reference value. The reference may represent the mean performance of skilled operators, a baseline condition, or a predefined industrial target. A value close to 1 indicates performance similar to the reference, whereas a value above 1 indicates that the evaluated operators required more time to understand the instructions. The ratio allows understanding performance to be compared across assembly tasks with different levels of complexity.

Execution Time Ratio (ETR) – compares the time required by the evaluated operators to execute an assembly task with a suitable reference value. For each assembly task *s*, it is calculated as:

$$MDR_s = \frac{\bar{T}_{E,s}}{\bar{T}_{E,s}^{Ref}} \quad (4)$$

where $\bar{T}_{E,s}$ is the mean Execution Time of the operators and $\bar{T}_{E,s}^{Ref}$ is the corresponding reference value. The reference may represent the mean performance of skilled operators, a baseline condition, or a predefined industrial target. Execution Time is used as a proxy for the manual demands associated with completing the assembly task. A value close to 1 indicates execution performance similar to the reference, whereas a value above 1 indicates slower execution. The ratio allows execution performance to be compared across assembly tasks with different manual requirements.

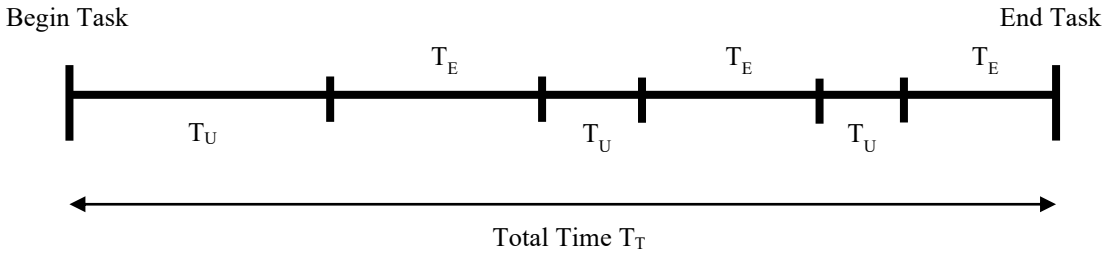


Fig 2 Schematic representation of Understanding, Execution Time, and Total Time

The proposed measures are organized into performance-related, quality-related, and Well-being-related Results. Performance-related outcomes concern productivity, learning progression, retention, and the ability to maintain performance over time. Quality-related outcomes concern assembly accuracy, procedural compliance, and error reduction. Well-being-related Results

concern the operator's cognitive effort, comprehension, independence, and reliance on external assistance. Table 2 integrates the KPIs identified in the literature with the measures proposed in this study.

Table 2 AR-Supported Capability Assessment Framework

Outcome Category	Capability	Consolidated Measure	Operationalization	Source
Performance	Selective Attention	T_U	Instruction-reading time	[30]; own development
		Attention Switches	Number of switches within the assembly workspace	[28]
		T_T	T_T under different visual-guidance conditions	[31]
	Memorization	Sequence Knowledge Accuracy	Assembly-sequence quiz accuracy after short-term retention interval	[28]
	Learning Ability	Assembly Errors	Change in errors across repeated assembly cycles	[29, 30]; own development
		T_U	Change in T_U across repeated assembly cycles	[30]; own development
		HR	Change in number of HR across repeated assembly cycles	Own development
	Knowledge Retention	Assembly Errors	Errors after a period without AR support	[29]; own development
		Sequence Knowledge Accuracy	Assembly-sequence quiz accuracy after one month	[28]
		T_U	Change in T_U after support removal	[30]; own development
		HR	Change in number of HR after support removal	Own development
	Working Velocity	T_E	Time spent completing assembly activities	Own development
		T_T	Overall task or assembly completion time	[21, 22, 28, 30, 31]; own development
	Manual Dexterity	MDR	T_E performance relative to reference level	Own development
Quality	Information Ordering	Assembly Errors	Assembly-order or sequencing errors	[20, 22]; own development
		Sequence Knowledge Accuracy	Assembly-sequence quiz accuracy	[28]
	Correctness	Assembly Errors	Number, rate, category, and severity of assembly errors	[20, 22, 29, 30]; own development
	Selective Attention	Assembly Errors	Tool- or part-selection errors	[22]; own development
Wellbeing	Selective Attention	T_U	Time required to consult and interpret AR instructions	[30]; own development
	Perceptual Speed	UTR	Understanding performance relative to a reference level	Own development
	Independence	HR	Number of requests for external assistance	Own development

	T_U	Reduction in reliance on instructions across repeated cycles	[30]; own development
	Assembly Errors	Errors after AR support is removed	[29]; own development
Visualization	Instruction comprehension	Questionnaire-based comprehension of assembly instructions	[31]

Beyond identifying the KPIs used to evaluate AR support for unskilled operators, it is also important to determine which assembly tasks may benefit from this technology. For simple tasks, AR may offer limited value and introduce unnecessary interaction time or complexity. To support this task-level analysis, the Cognitive Demand Index (CDI) and the Operational Difficulty Index (ODI) were introduced to identify cognitive and operational difficulties, respectively.

Cognitive Demand Index (CDI) – to identify assembly tasks that may impose greater cognitive demands on individual operators. It builds on the index proposed by Loizeau et al. [33] and applied by Dallasega et al. [34]. For each operator i and assembly task s, the CDI is calculated as:

$$CDI_{i,s} = \frac{T_{U,i,s}}{\bar{T}_{E,s}} + \theta * HR_{i,s} \quad (5)$$

where $T_{U,i,s}$ and $\bar{T}_{E,s}$ are the Understanding Time and Execution Time recorded for operator i during task s, and $HR_{i,s}$ is the number of Help Requests for the same task. θ represents the threshold above which the operation is defined as *Cognitively Demanding*. A higher CDI indicates that the operator required more time to understand the instructions relative to the typical execution time of the task. An operator-task observation is classified as *Cognitively Demanding* when its CDI exceeds a predefined threshold θ or when the operator records at least one Help Request:

$$CD_{i,s} = \begin{cases} cognitively\ demanding,\ if\ CDI_{i,s} > \theta\ or\ HR_{i,s} \geq 1 \\ not\ cognitively\ demanding,\ if\ CDI_{i,s} \leq \theta\ and\ HR_{i,s} = 0 \end{cases} \quad (6)$$

The threshold θ should be defined according to the application context using a suitable reference group, historical process data, or predefined industrial criteria. For example, in the benchmark study presented in this paper, the threshold θ was set at the 75th percentile of the CDI distribution obtained from the reference group, so that observations exceeding the value typically recorded for 75% of the reference observations were classified as *Cognitively Demanding*.

Operational Difficulty Index (ODI) – is a binary indicator used to determine whether an operator encounters execution difficulties during an assembly task. For each operator i and task s, the ODI considers both the number and severity of the recorded assembly errors. Minor errors (m) have a weight of 0.5, whereas Major errors (M) have a weight of 1. The ODI is defined as:

$$ODI_{i,s} = \begin{cases} 1,\ if\ 0{,}5m_{i,s} + M_{i,s} \geq 1 \\ 0,\ if\ 0{,}5m_{i,s} + M_{i,s} = 0 \end{cases} \quad (7)$$

The CDI and ODI can be combined to classify each operator-task observation into four categories: *Standard, Cognitively Demanding, Operationally Demanding*, and *Critical*. Comparing this classification across AR-assisted and reference conditions helps identify tasks that benefit from AR, tasks that require additional support, and simple tasks for which AR may introduce unnecessary complexity or reduce performance.

3.3. Experimental Design and Procedure

Based on the AR-Supported Capability Assessment Framework developed in Section 3.2 and summarized in Table 2, a benchmark study examined whether AR-assisted unskilled operators could approach the task-level performance of experts using conventional instructions. An AR application guided participants through the assembly and wiring of an electrical control panel provided by a manufacturer of electrical and electronic components. The case combined technical documentation interpretation with precise positioning and wiring operations, covering cognitive, technical, and practical requirements. Thirteen employees participated voluntarily: six qualified electricians who regularly assembled electrical panels and seven unskilled operators with no previous experience in this activity. The sample included five women and eight men, six participants under 30 and seven over 55, including two with a migrant background. None had previous AR experience. All participants received information about the procedure and provided written informed consent.

As shown in Figure 3, the experiment included preparation, assembly, and post-assembly assessment. The unskilled operators received approximately 20 minutes of familiarization with Microsoft HoloLens 2 and the AR application, while the experts were introduced to the revised paper instructions. During assembly, the unskilled operators followed task-by-task AR guidance, whereas the experts used paper instructions covering the same tasks and sequence. Understanding Time, Execution Time, Assembly Errors, and Help Requests, as defined in Section 3.2, were recorded for each task. After assembly, only the unskilled operators completed a theoretical knowledge quiz, the NASA Task Load Index (NASA-TLX), and the System Usability Scale (SUS) to assess acquired knowledge, perceived workload, and system usability.

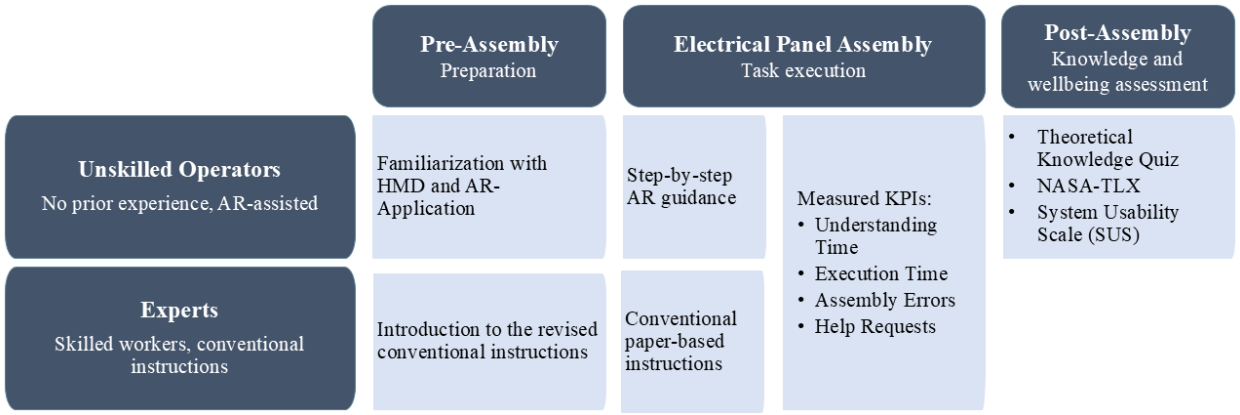


Fig. 3 Experimental design of the benchmark study

Table 3 links the selected capabilities to their assessment methods, distinguishing between positioning (Tasks 1–10), wiring (Tasks 11–20), and the overall procedure.

Positioning mainly involved *Selective Attention*, *Technical Understanding*, and *Learning Ability*. *Selective Attention*, required to identify components and verify their codes, was assessed through Question 4 of the theoretical knowledge quiz and wrong-component errors. *Technical Understanding* was relevant to specific requirements, including aligning the main switch with the cabinet door (Task 1), fastening grounding terminals to the DIN rail (Task 4), and installing protective covers (Tasks 8 and 10). It was assessed through Questions 1 and 5–7 of the quiz (Appendix A). *Learning Ability* was evaluated through changes in Understanding Time (TU) across similar component-clipping operations (Tasks 3, 5, 7, and 9), with decreasing TU indicating progressive learning.

Wiring mainly involved *Manual Dexterity* and *Technical Understanding*. *Manual Dexterity* was assessed by comparing Execution Time (TE) with the expert reference and examining changes in the performance gap across wiring tasks. *Technical Understanding* was required for installing diodes and resistors and completing complex wiring operations (Tasks 15, 16, and 19) and was assessed through Questions 2 and 3 of the quiz.

Across the entire procedure, *Correctness* was assessed through assembly errors, *Independence* through Help Requests, *Perceptual Speed* through TU, and *Working Velocity* through TE. Time-based measures were compared with expert performance.

Measurements were coded through direct observation by two observers for each group. TU and TE values were compared and averaged, while disagreements concerning errors, severity, and Help Requests were resolved conservatively by retaining the highest recorded value. *Memorization* and *Information Ordering* were excluded because the assembly did not follow a single mandatory sequence. *Knowledge Retention* was not assessed because unskilled operators would have required additional training before repeating the complex assembly without AR guidance.

Table 3 Summary of the capabilities considered in the assembly task and the corresponding assessment methods

Capability	Assembly Phase	Tasks	Role in the Task	Assessment Method
Selective Attention	Positioning	1-10	Component Identification	Theoretical Knowledge Quiz (Q4) + Assembly Errors (wrong component)
Technical Understanding	Positioning	1,4,8,10	Technical Assembly Requirements	Theoretical Knowledge Quiz (Q1, Q5-Q7)
Learning Ability	Positioning	3,5,7,9	Learning from repetition of similar tasks	Understanding Time Ratio (UTR) trend
Manual Dexterity	Wiring	11-20	Wire manipulation and cabling	Execution Time Ratio (ETR) trend
Technical Understanding	Wiring	15,16,19	Technical Wiring Requirements	Theoretical Knowledge Quiz (Q2, Q3), Assembly Errors
Correctness	Overall	1-20	Assembly Accuracy	Assembly Errors
Independence	Overall	1-20	Task autonomy	Help requests

Perceptual Speed	Overall	1-20	Task comprehension	Understanding Time T_U
Working Velocity	Overall	1-20	Task Execution	Execution Time T_E

3.4. Description of AR Application

Microsoft HoloLens 2 was used as the head mounted display (HMD), while the AR application was developed using Unity 2021.3.21f1, MRTK3, and OpenXR. Available 3D models of the electrical cabinet components were collected, while nonstandard parts were recreated in Autodesk Inventor. The complete cabinet was then reconstructed in Unity. For each assembly task, the application displays the required components and instructions as holograms. A QR code placed on the inclined cabinet support provides the spatial reference needed to align the virtual content with the physical workstation. Users navigate through the procedure using a virtual control panel that supports remote activation, direct hand interaction, and voice commands. Voice interaction was recommended when both hands were occupied, while a status indicator displayed the current task. During component placement, holograms indicate the correct position of each part. An image of the identification code helps users select components by shape and part number, while colours distinguish component types. Animations illustrate component installation and any required preliminary operations. During wiring, cable holograms show the required route and reproduce the colour and diameter of the physical cables. Cable and port codes identify the required connections, while yellow arrows indicate starting, ending, and intermediate routing points. When a connection has no unique port code, the terminal strip is shown as a semi-transparent hologram with the required terminal highlighted. Blue panels provide additional information for operations requiring particular attention. Figure 4 shows the AR instructions from the end user's perspective.

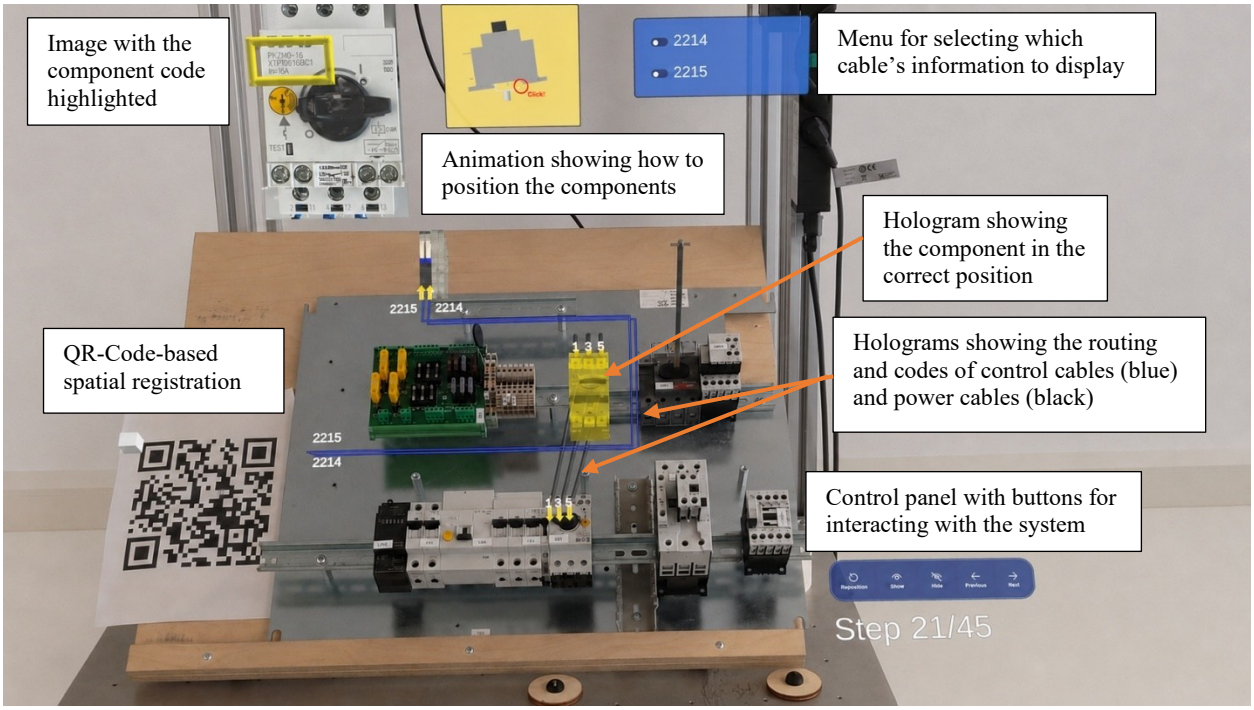


Fig. 4 Structure of the instructions displayed through Microsoft HoloLens 2 during the positioning and wiring phases

4. Case study application

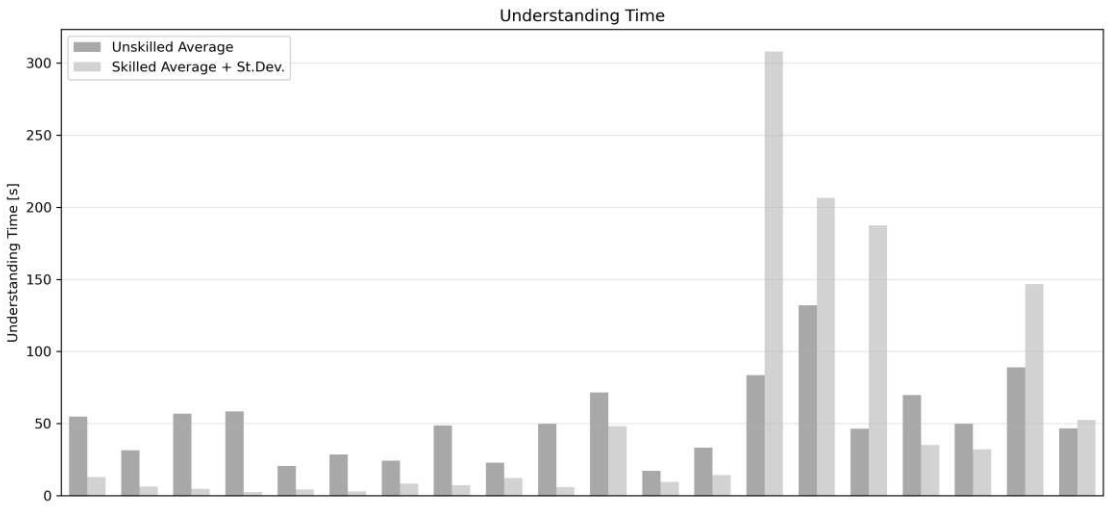
The AR-Supported Capability Assessment Framework presented in Section 3.2 and summarized in Table 2 was applied to the electrical-panel assembly case study. Based on the capabilities involved in the investigated tasks, the relevant framework indicators were selected and measured. The following sections present the results obtained from applying these indicators.

Performance-related Results

Understanding time: Figure 5 presents the average Understanding Time (TU) of AR-assisted unskilled operators across the 20 assembly tasks, together with the expert benchmark. The positioning phase (Tasks 1–10) involved identifying components by geometry and identification code and placing them correctly on the assembly base. The wiring phase (Tasks 11–20) involved connecting the components through cables.

A clear difference emerged between the two phases. During positioning, unskilled operators generally recorded higher TU than experts. During wiring, however, their TU was more stable, while expert values fluctuated and, in some tasks, exceeded those of the unskilled group. AR-assisted unskilled operators recorded shorter TU than experts in Task 14 (wiring of the motor protection and contactor), Task 15 (power supply wiring), Task 16 (Molex 3901-2240 wiring, Part 2), Task 19 (wiring of 2201 and 2202), and Task 20 (wiring of RL1, RL2, RL3, and RL4).

During wiring, the AR application provided direct and intuitive task-by-task guidance. Experts instead used conventional paper instructions in which the same tasks were highlighted and numbered to ensure that both groups followed the same assembly order and logic. However, the experts still had to interpret electrical schematics distributed across multiple pages before identifying the required wiring sequence, which resulted in higher TU for some wiring tasks.



Step	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Unskilled Average	54.9	31.4	56.8	58.5	20.5	28.6	24.2	48.6	22.9	49.9	71.6	17.1	33.4	83.6	132.0	46.4	69.8	49.8	89.1	46.7
Skilled Average + St.Dev.	12.9	6.3	4.7	2.6	4.2	2.9	8.4	7.2	12.3	5.8	48.3	9.5	14.3	308.0	206.6	187.5	35.0	32.2	146.8	52.5

Fig. 5 Understanding time T_U comparison between experts (light grey) and unskilled operators (dark grey)

Following the Understanding Time T_U analysis, *Learning Ability* was evaluated by examining the trend of the Understanding Time Ratio (UTR), defined in Section 3.2 and Equation (3), across comparable assembly tasks. The UTR expresses the average Understanding Time of unskilled operators relative to that of expert participants. Therefore, a decreasing trend indicates that the performance gap becomes smaller over successive tasks, suggesting a learning effect. This analysis was limited to tasks 3, 5, 7, and 9 because they involved the same core activity, namely clipping components onto the support. Comparing similar operations reduces the influence of differences in task complexity. As shown in Table 4, the UTR decreased from 18.93 in task 3 to 3.81 in task 9, suggesting progressive learning across the selected tasks.

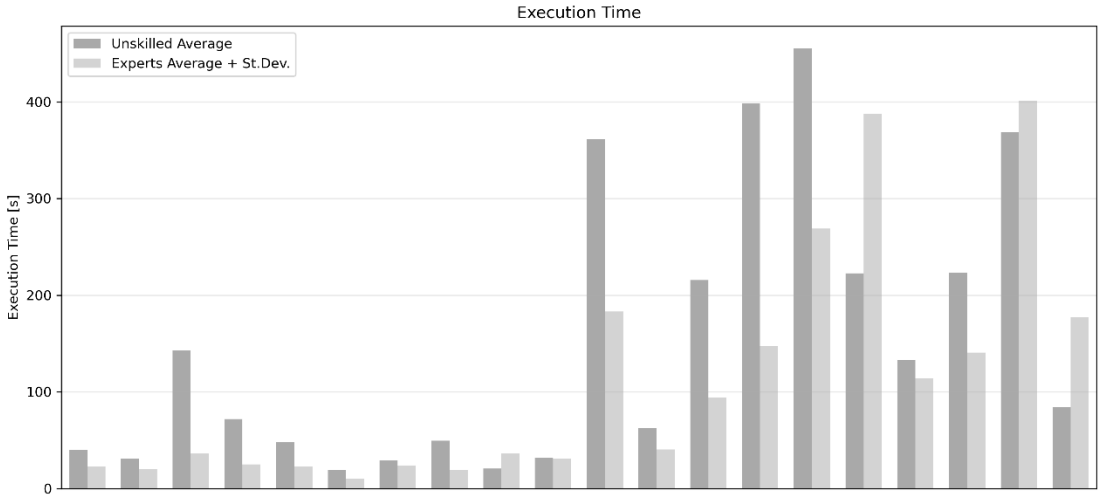
Table 4 Understanding Time Ratio (UTR) Trend for tasks 3, 5, 7, 9

Task	3	5	7	9
Understanding Time Ratio	18.93	8.79	5.39	3.81

Execution time: Figure 6 compares the average Execution Time (TE) of AR-assisted unskilled operators and experts across the 20 assembly tasks. TE is expressed in seconds on the y-axis, while the tasks and their average values are shown on the x-axis.

As with TU, different patterns emerged between positioning (Tasks 1–10) and wiring (Tasks 11–20). During positioning, the two groups recorded generally comparable TE, with only limited differences. During wiring, however, AR-assisted unskilled operators completed several operations faster than experts, particularly Task 16 (Molex 3901-2240 wiring, Part 2), Task 19 (wiring of 2201 and 2202), and Task 20 (wiring of RL1, RL2, RL3, and RL4).

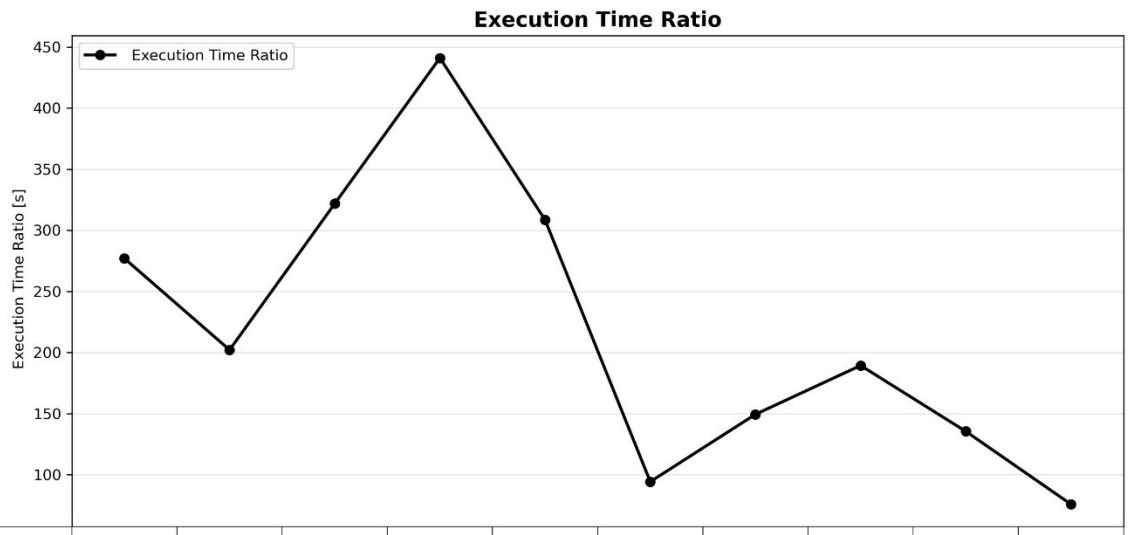
Larger differences occurred in cabling operations involving connector mechanisms unfamiliar to the unskilled operators. Nevertheless, AR guidance enabled them to complete several complex wiring tasks in times comparable to or shorter than the expert benchmark, with differences of up to 60 seconds. Experts adopted a broader strategy that considered cable positioning for subsequent tasks, the overall panel layout, and order-specific requirements. In contrast, unskilled operators followed sequential AR guidance and focused on the immediate operation.



step	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Unskilled Average	40.1	31.1	142.8	72.1	47.8	19.4	29.2	49.5	20.9	31.8	361.4	62.7	215.6	398.4	455.5	222.6	133.0	223.1	368.9	84.1
Experts Average + St.Dev.	23.1	20.2	36.3	25.2	22.7	9.9	24.2	19.1	36.4	31.0	183.2	40.4	94.3	147.7	269.0	387.4	114.2	140.6	401.0	177.6

Fig. 6 Execution time T_E comparison between experts (light grey) and AR-assisted unskilled operators (dark grey)

Manual Dexterity was assessed using the Execution Time Ratio (ETR), calculated as the ratio between the average execution time of the unskilled operators and that of the experts for the cabling tasks (tasks 11–20), defined in Section 3.2 and Equation (4). A decreasing score indicates that the execution performance of the unskilled operators progressively approaches that of the experts. Figure 7 presents the ETR for each cabling task. An overall decreasing trend can be observed throughout the cabling phase, indicating a progressive reduction in the execution time T_E difference between the unskilled operators and experts across successive wiring operations.

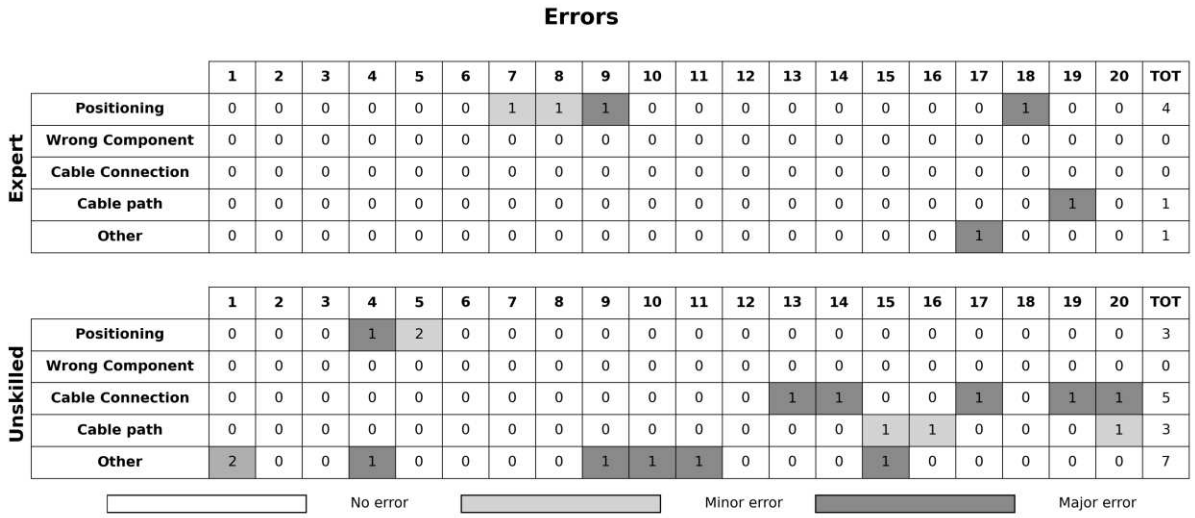


Step	11	12	13	14	15	16	17	18	19	20
Execution Time Ratio	277.0	202.1	321.8	441.0	308.5	94.2	149.4	189.3	135.4	75.8

Fig. 7 Execution Time Ratio (ETR) for the wiring phase (Tasks 11-20)

Quality-related Results

Assembly errors: Assembly errors were classified into five categories: i) “positioning”, ii) “wrong component”, iii) “cable connection”, iv) “cable path”, and v) “others”. Each error was also classified as minor, when it did not compromise correct functioning, or major, when it affected the operation of the electrical cabinet. Figure 8 presents the number and severity of errors recorded for both groups across assembly tasks and categories. AR assisted unskilled operators performed better during component positioning than during wiring, whereas experts made fewer cable connection errors, particularly in Tasks 13–16 and 20. AR overlays effectively supported component positioning, while occasional misalignments between virtual and physical elements contributed to wiring errors. Errors classified as “others” mainly concerned tool handling and component locking mechanisms during cable insertion and coupling.

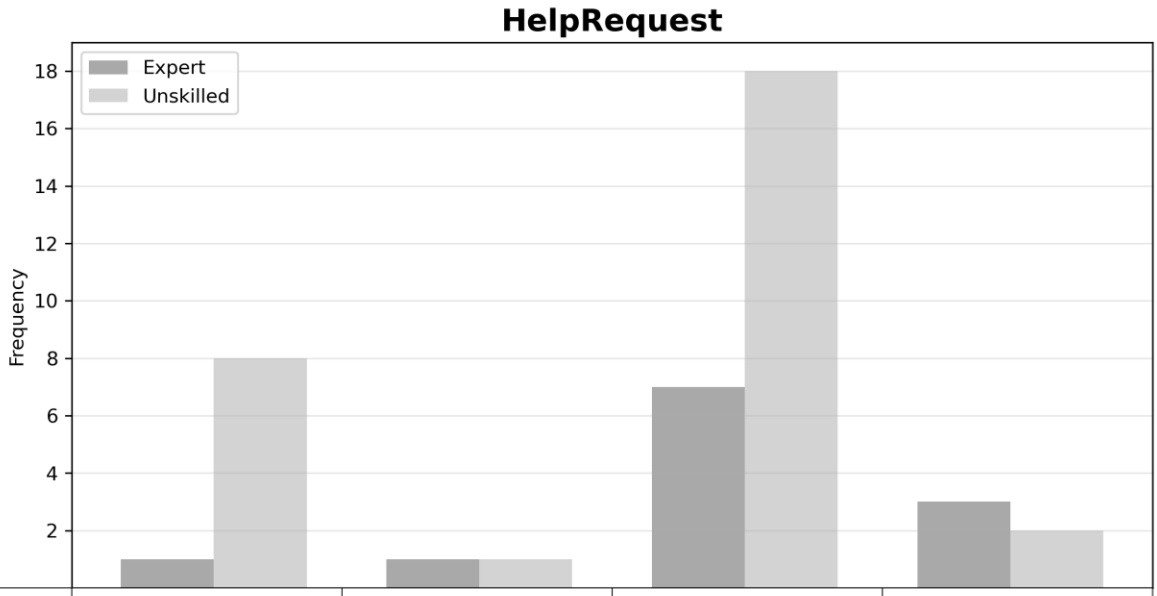


Expert	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	TOT
Positioning	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	1	0	0	4
Wrong Component	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cable Connection	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cable path	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
Other	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1

Unskilled	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	TOT
Positioning	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
Wrong Component	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cable Connection	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	1	1	5
Cable path	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	3
Other	2	0	0	1	0	0	0	0	1	1	1	0	0	0	1	0	0	0	0	0	7

Fig. 8 Comparison of assembly errors between experts (upper part) and unskilled operators (lower part). The heatmap reports the number of errors for each assembly task and error category, while the colour intensity indicates error severity.

Help Request: Requests for clarifications of instructions have been noted and recorded. Easier visualization was pursued by classifying the help requests in similar classes as the errors (Fig. 9): it is to be noted the omission of the ‘wrong component’ class, due to a substantial lack of help requests in that department.



Help group	Component positioning	Connections	Cable positioning	Other
Expert	1	1	7	3
Unskilled	8	1	18	2

Fig. 9 Comparison of help requests for Experts (dark grey) and Unskilled operators (light grey), classified by help group (Component Positioning, Connections, Cable Positioning, Other)

Quiz results: Knowledge acquisition was assessed through the quiz included in Appendix A. The score assigned to each question reflected the number of correct answers required. For example, component code recognition was worth four points because participants had to identify four codes. Table 5 reports the total errors made by unskilled operators for each question. Most errors concerned component codes and their electrical specifications, such as AC/DC type and voltage. During assembly, participants mainly identified components by shape and colour rather than by code, which may explain their poorer performance on these questions.

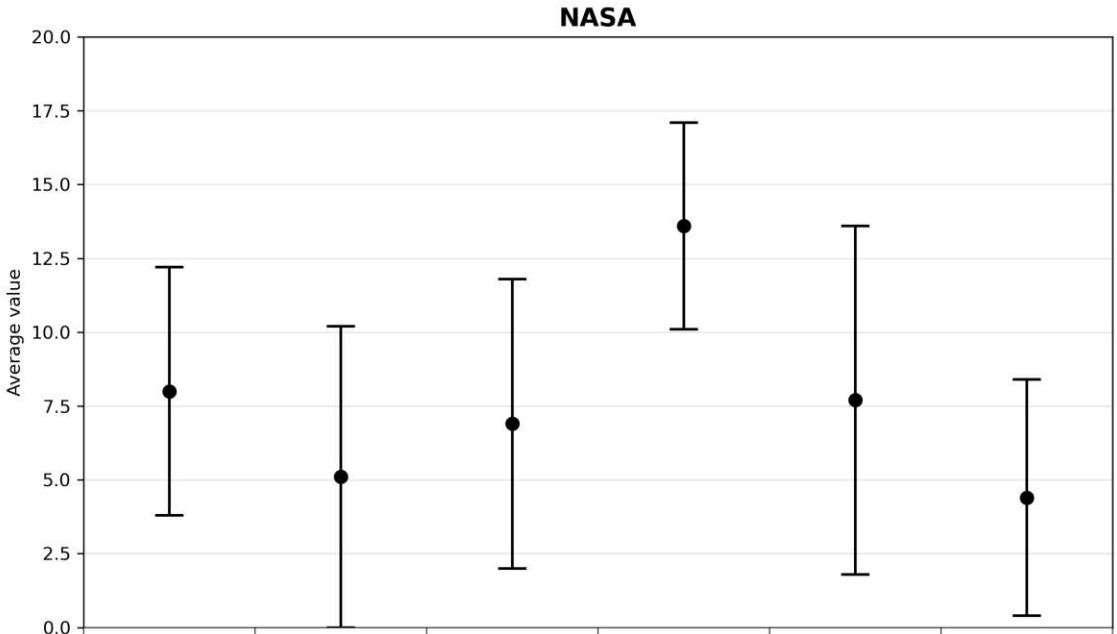
Table 5 Compound errors in the quiz results by unskilled workers

No.	Question of quiz	# of errors
1	Why is it important to install the covers on certain terminal blocks?	0
2	Which of the following pictures shows a diode/resistor?	1
3	Where should the diodes/resistors be routed?	1
4	Highlight on the images the information which are most important	14
5	To which of the presented items is the positioning most important?	2
6	Which of the following clamps needs to be fixed with a screwdriver?	0

7	Why must this terminal block be fastened to the DIN rail using a screwdriver?	1

Well-being-related Results

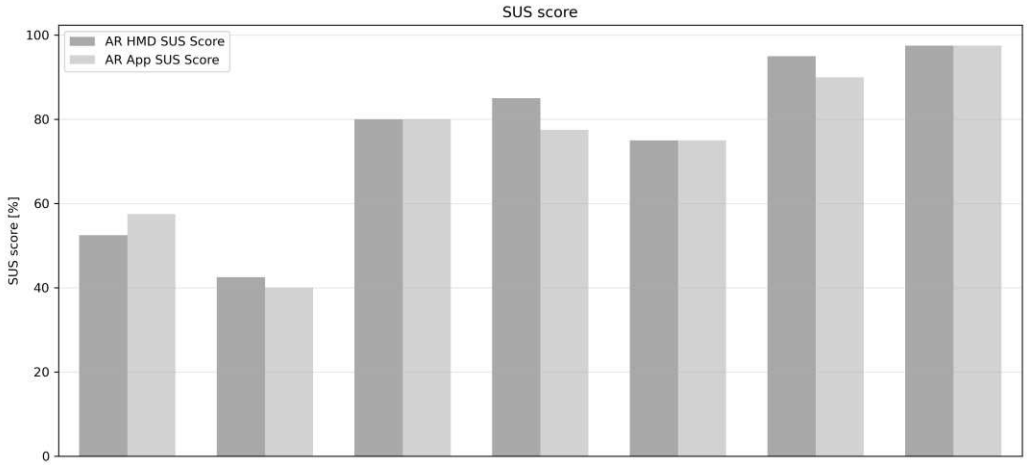
NASA-TLX: Figure 10 presents the NASA Task Load Index (NASA-TLX) results for the AR-assisted unskilled operators. The figure reports the average score for each of the six workload dimensions (mental demand, physical demand, temporal demand, performance, effort, and frustration) while the intervals represent the standard deviation across participants. Overall, the results indicate a relatively low perceived workload during the assembly task. Low scores were observed for mental demand, physical demand, temporal demand, effort, and frustration, whereas the participants reported high perceived performance, suggesting that they felt confident in successfully completing the assembly task.



	Mental Demand	Physical Demand	Temporal Demand	Performance	Effort	Frustration
AVG	8.0	5.1	6.9	13.6	7.7	4.4
StDev	4.2	5.1	4.9	3.5	5.9	4.0

Fig. 10 NASA-TLX results for the AR-assisted unskilled operators. The markers represent the average score for each workload dimension, while the error bars indicate the standard deviation

System Usability Scale (SUS): Figure 11 presents the SUS scores for the HMD and AR application for each unskilled operator. The scores were calculated using the standard SUS procedure [35, 36], with approximately 68 representing average usability. Scores above 80 indicate excellent usability, scores between 68 and 80 good usability, scores between 51 and 67 sufficient usability, and scores below 50 critical issues. Most participants reported good usability (three participants) or excellent usability (two participants). One participant reported below average usability, while another reported sufficient usability. Overall, most participants perceived the setup as easy to use. However, the lower scores reported by two participants suggest that a longer familiarization phase could improve the user experience.



Unskilled worker #	1	2	3	4	5	6	7
AR HMD SUS Score	52.5	42.5	80.0	85.0	75.0	95.0	97.5
AR App SUS Score	57.5	40.0	80.0	77.5	75.0	90.0	97.5

Fig. 11 System Usability Score for both AR-Glasses (dark grey) and AR-Application (light grey)

Assembly task classification based on cognitive demand and operational difficulty

To provide a more detailed analysis of the cognitive and operational demands associated with individual assembly tasks, a task-level classification was developed by combining two complementary dimensions: cognitive demand and operational difficulty. The detailed list of assembly tasks is included in attachment 2. The Cognitive Demand Index (CDI), defined in Section 3.2 and Equations (5)-(6), was used to quantify the cognitive demand associated with each assembly-task observation. The cognitive-demand threshold was determined as the 75th percentile of the normalized Understanding Time distribution of the expert group, corresponding to a value of 0.39. As illustrated in Figure 12, this threshold separates observations requiring a level of cognitive effort comparable to that typically experienced by expert operators from those associated with higher cognitive demand. The same threshold was subsequently adopted as a common benchmark for both expert and unskilled participants. Consequently, the CDI for each observation was calculated as:

$$CDI_{i,s} = \frac{T_{U,i,s}}{\bar{T}_{E,s}} + 0{,}39 \times HR \quad (8)$$

where $T_{U,i,s}$ is the Understanding Time recorded for the operator i during assembly task s, $\bar{T}_{E,s}$ is the mean Execution Time of the corresponding participant group (expert or unskilled) for the same assembly task, and HR is the number of help requests recorded for the corresponding observation.

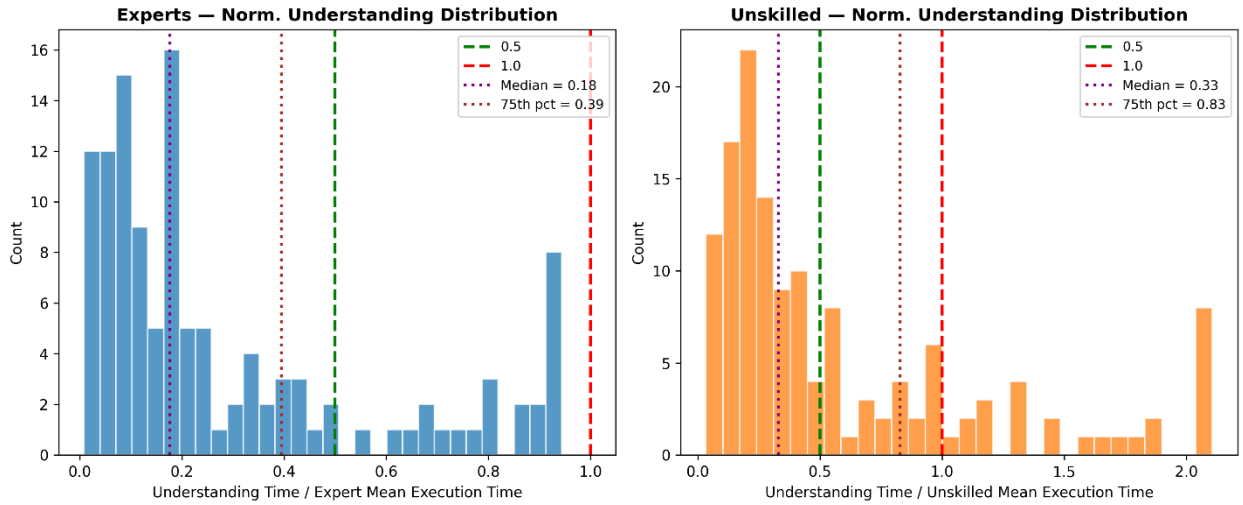


Fig. 12 Distribution of the normalised understanding-time and expert-derived cognitive demand threshold.

Operational difficulty was evaluated using the Operational Difficulty Index (ODI), which identifies whether at least one execution error occurred during an assembly task, as defined in Section 3.2 and Equation (7). The CDI and ODI were then combined to classify each observation into four categories:

- **Standard:** low cognitive demand and no errors;
- **Cognitively Demanding:** high cognitive load and no errors;
- **Operationally Demanding:** low cognitive load and at least one error;
- **Critical:** high cognitive load and at least one error.

Observations with at least one Help Request are represented by triangles (▲), distinguishing help-related cognitive demand from elevated CDI caused solely by longer Understanding Time (TU). Figure 13 presents the resulting classification. Most expert observations were concentrated in the *Standard* quadrant, indicating low cognitive demand and no execution errors. Fewer observations showed high cognitive load without errors. *Critical* observations occurred only in Tasks 9 and 19, while *Operationally Demanding* observations occurred in Tasks 17 and 18.
The unskilled group showed a broader distribution across the four categories, with more observations in the high cognitive load quadrant. *Critical* observations occurred in Tasks 4, 10, 11, 15, 17, 19, and 20, while *Operationally Demanding* observations were less frequent. Overall, elevated cognitive demand with error-free execution was more common among unskilled operators, whereas observations involving errors were distributed between the *Operationally Demanding* and *Critical* categories.

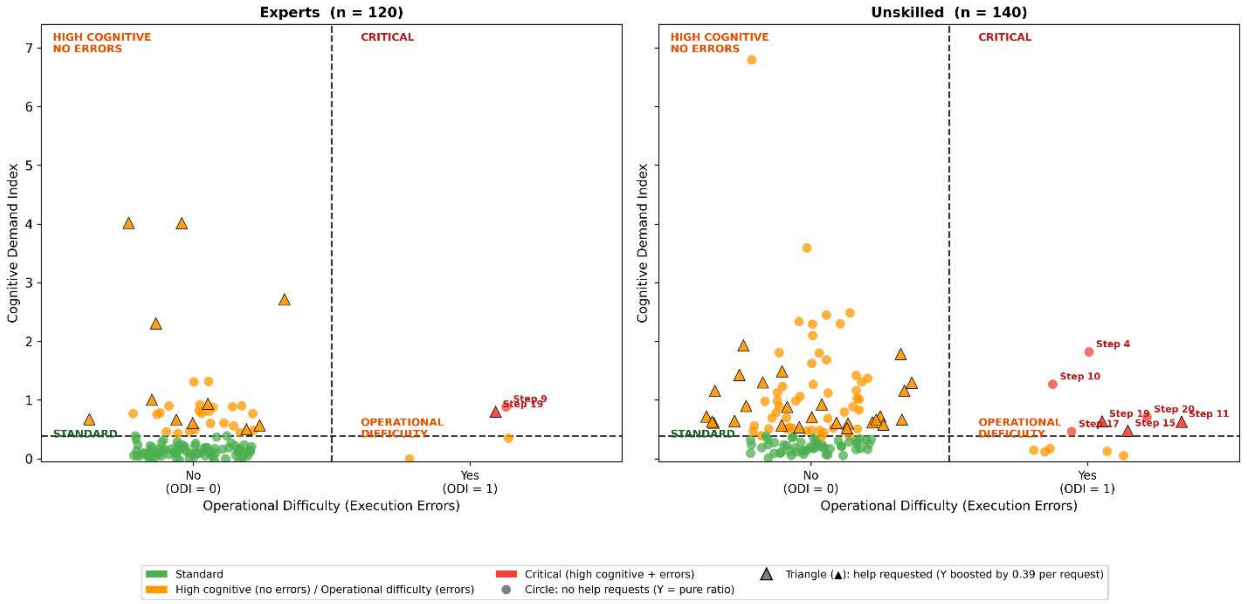


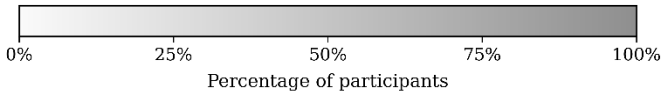
Fig. 13 Task-level classification of expert and unskilled operators based on cognitive demand and operational difficulty

The task-level distribution of the four classification categories is summarized in Table 6. For the expert group, *Standard* was the predominant classification across the positioning tasks, accounting for at least 67% of observations in tasks 1–10. A different pattern emerged for several wiring tasks, particularly tasks 14, 15, 16, and 19, where high cognitive load accounted for 83%, 50%, 67%, and 50% of observations, respectively. Critical classifications were limited to tasks 9 and 19 (17%), while operational difficulty occurred only in tasks 17 and 18 (17%).

For the unskilled group, high cognitive load was more prevalent across the positioning tasks, reaching 100% in task 6 and 71% in several other tasks. The wiring tasks showed a more heterogeneous distribution: some tasks were predominantly *Standard*, such as tasks 13 and 16 (86%), whereas others showed a high proportion of high cognitive load, particularly tasks 14 and 17 (71%). Critical classifications occurred in both positioning and wiring tasks, while operational difficulty was observed in a limited number of tasks.

Table 6 Task-level classification of experts and unskilled operators across assembly operations (values represent the percentage of participants in each classification category)

	Step	Experts				Unskilled			
		STD	HIGH-COG	OP-DIFF	CRIT	STD	HIGH-COG	OP-DIFF	CRIT
Positioning	1	83%	17%	–	–	29%	57%	14%	–
	2	83%	17%	–	–	29%	71%	–	–
	3	100%	–	–	–	29%	71%	–	–
	4	83%	17%	–	–	14%	57%	14%	14%
	5	67%	33%	–	–	43%	57%	–	–
	6	83%	17%	–	–	–	100%	–	–
	7	67%	33%	–	–	29%	71%	–	–
	8	83%	17%	–	–	29%	71%	–	–
	9	67%	17%	–	17%	14%	71%	14%	–
	10	67%	33%	–	–	14%	71%	–	14%
Wiring	11	67%	33%	–	–	43%	43%	–	14%
	12	83%	17%	–	–	71%	29%	–	–
	13	100%	–	–	–	86%	–	14%	–
	14	17%	83%	–	–	14%	71%	14%	–
	15	50%	50%	–	–	57%	29%	–	14%
	16	33%	67%	–	–	86%	14%	–	–
	17	67%	17%	17%	–	14%	71%	–	14%
	18	67%	17%	17%	–	57%	43%	–	–
	19	33%	50%	–	17%	43%	43%	–	14%
	20	67%	33%	–	–	43%	43%	–	14%



5. Discussion

5.1 Effectiveness of AR in supporting unskilled workers during industrial assembly

To answer the first research question, AR-assisted unskilled operators approached the expert paper-based benchmark in several assembly operations, although they generally experienced higher cognitive demand. Contextual guidance supported the interpretation of unfamiliar instructions and procedural execution, but its effectiveness varied by task. Outcomes were more favourable for operations involving information interpretation and procedural guidance than for those requiring technical knowledge and practical experience.

AR facilitated procedural learning during task execution. Although unskilled operators generally required longer understanding and execution times than experts (Figures 5 and 6), several observations showed high cognitive demand without execution errors. Operators therefore often required greater effort to interpret instructions but still executed the operations correctly. By presenting contextual information in the workplace, AR supported unfamiliar procedures, although cognitive demand remained higher than the expert benchmark [15, 37].

AR supported workers during an unfamiliar assembly task. NASA-TLX results (Figure 10) showed moderate mental demand and effort but relatively low frustration, despite participants having no previous electrical-panel assembly experience. Contextual guidance may therefore have helped them manage the unfamiliar procedure without excessive perceived workload while reducing the need to consult separate instructions.

AR supported procedural execution during positioning tasks. The task-level classification (Figure 13 and Table 6) frequently identified *High Cognitive Load* among unskilled operators during positioning, while *Operational Difficulty* and *Critical* observations were less common. Their main challenge was therefore understanding the instructions rather than executing the

physical operation. Once the required action was identified, most tasks were completed without errors, suggesting that holographic overlays supported component identification and positioning.

During wiring, *Operational Difficulty* and *Critical* observations became more frequent (Figure 13 and Table 6). These tasks required operators to identify cables and terminals and complete connections according to electrical specifications, involving *Technical Understanding* beyond procedural guidance. Nevertheless, several unskilled operators completed demanding Tasks 14, 15, 16, and 19 without errors or Help Requests. AR therefore supported some procedural demands of complex wiring, although the remaining *Critical* observations confirm the importance of technical knowledge and experience.

Overall, AR appeared to support information location and procedural demands more effectively than experience dependent manual skills or domain specific reasoning. This distinction helps explain the mixed findings concerning task complexity and AR effectiveness [14–18]. The relevant factor may not be complexity alone, but the underlying capability requirements and whether contextual information can support them. This proposition should be tested across different assembly processes and larger samples.

In response to RQ1, AR-assisted unskilled operators approached the expert paper-based benchmark in selected tasks, but remaining differences depended on task requirements. The relationship between worker capabilities and AR-assisted performance is examined in the following section.

5.2 Human capabilities and the effectiveness of AR support

To answer RQ2, the benchmark results were interpreted using the AR-Supported Capability Assessment Framework presented in Section 3.2 and Table 2. For each electrical-panel assembly task, the relevant worker capabilities were identified from its operational requirements, and the corresponding KPIs were measured for each operator. The resulting operator–task observations were classified as *Standard*, *High Cognitive Load*, *Operational Difficulty*, or *Critical* according to their cognitive and operational demands.

The analysis focused on tasks with predominantly non-*Standard* observations. A task was considered demanding for AR-assisted unskilled operators when no more than one of seven observations was *Standard*, identifying Tasks 4, 6, 9, 10, 14, and 17. For experts, tasks were selected when half or fewer observations were *Standard*, identifying Tasks 14, 15, 16, and 19. Combining both criteria resulted in nine tasks: 4, 6, 9, 10, 14, 15, 16, 17, and 19. Table 7 compares the proportion of *Standard* observations between groups and identifies the relevant capabilities for each task. Lower rates among unskilled operators indicate a remaining gap from the expert benchmark, while similar rates indicate comparable outcomes. Low rates in both groups suggest that the task was demanding regardless of experience, whereas higher rates among unskilled operators indicate more favourable outcomes. These comparisons are descriptive and should not be interpreted as direct evidence of AR effectiveness.

Table 7 Comparison of representative assembly tasks according to the expert benchmark, unskilled-operator performance, and distinctive capability requirements.

Task	Standard Experts	Standard Unskilled	Distinctive Capabilities	Comparative Interpretation
4	83%	14%	Selective Attention; Technical Understanding	Large remaining performance gap

6	83%	0%	Selective Attention	Large remaining performance gap
9	67%	14%	Selective Attention; Learning Ability	Remaining gap despite evidence of learning
10	67%	14%	Selective Attention; Technical Understanding	Large remaining performance gap
14	17%	14%	Manual Dexterity	Inherently demanding for both groups
15	50%	57%	Manual Dexterity; Technical Understanding	Similar Standard rate, but mixed results
16	33%	71%	Manual Dexterity; Technical Understanding	Strongest indication of effective AR support
17	67%	14%	Manual Dexterity	Large remaining performance gap
19	33%	43%	Manual Dexterity; Technical Understanding	Performance close to the expert benchmark

Tasks in which unskilled operators approached or exceeded the expert benchmark. The most favourable outcomes for AR-assisted unskilled operators occurred in Tasks 15, 16, and 19. These wiring operations combined *Technical Understanding* and *Manual Dexterity*, requiring operators to interpret electrical configurations, identify connection points, route cables, and manipulate components.

Task 16, involving an electrical component connection, showed the largest positive difference. *Standard* observations accounted for 71% among AR-assisted unskilled operators and 33% among experts. By displaying components, connection points, and routing information directly in the workplace, AR may have supported the interpretation and execution of this operation.

In Task 19, involving complex multiple connection wiring, *Standard* observations were also slightly higher among unskilled operators than experts, at 43% and 33%, respectively. Contextual guidance may have supported the identification of connections and cable routes, although the difference was smaller than in Task 16.

Task 15 involved a cable connection and resistor positioning within the wiring duct and produced more heterogeneous results. *Standard* observations were similar between groups, at 57% for unskilled operators and 50% for experts. However, two unskilled observations were *Critical*, compared with none among experts. AR may therefore have supported some operators, while differences in *Technical Understanding*, *Manual Dexterity*, and instruction interpretation remained relevant.

These findings suggest that contextual AR guidance may support operations combining technical and manual requirements when the necessary information is presented clearly. However, similar capability profiles did not always produce comparable outcomes, highlighting the importance of the specific operational demands.

Tasks that were easy for experts but difficult for unskilled operators. Tasks 4, 6, 9, 10, and 17, described in Appendix B, were predominantly *Standard* for experts but remained demanding for AR-assisted unskilled operators. Their capability requirements help explain these gaps.

Task 4 involved installing and securing a protective earth terminal block and required operators to understand the importance of establishing proper electrical contact. Task 10 involved installing terminal blocks and a lateral protective cover to prevent unintended electrical contact. In both tasks, AR provided positioning and procedural guidance, but *Technical Understanding* and practical judgement remained important.

Task 17 involved connecting a relay contactor to a control board and required precise wire handling and positioning. Although AR displayed connection points and cable routes, physical execution remained dependent on *Manual Dexterity* developed through experience.

Tasks 6 and 9 presented a different pattern. Relay positioning in Task 6 and the positioning of two terminal blocks in Task 9 primarily involved *Selective Attention* and, in Task 9, *Learning Ability*, rather than complex technical reasoning or manual actions. Their high cognitive demand suggests that detailed AR guidance did not eliminate the classification gap and may have introduced additional processing or interaction demands. Nevertheless, the decreasing Understanding Time Ratio across comparable positioning activities indicates that operators became more efficient at interpreting AR instructions, even though Task 9 remained demanding relative to the benchmark.

Tasks that were demanding for both groups. Task 14, involving the interpretation and connection of electrical terminals, was demanding for both groups. Only 17% of expert observations and 14% of unskilled observations were *Standard*. The operation required *Manual Dexterity* and the general capabilities involved in wiring, suggesting that its difficulty reflected intrinsic operational demands rather than the instructional medium alone. Despite their limited experience, AR-assisted unskilled operators achieved outcomes comparable to experts. AR did not eliminate the task difficulty, but contextual guidance may have helped them complete the operation. The low *Standard* rates in both groups nevertheless indicate that the guidance could be improved.

Previous research shows that AR effectiveness varies with task complexity [14–18]. However, the present findings indicate that complexity alone does not explain AR-assisted performance. Tasks with similar difficulty produced different outcomes depending on their capability requirements. AR appeared more useful for information location and procedural demands than for technical reasoning or experience dependent manual skills.

These findings support the proposition that AR effectiveness depends on the capability profile of each task and whether its requirements can be addressed through contextual digital information. This capability-based interpretation represents the main theoretical contribution of the AR-Supported Capability Assessment Framework, although validation across other assembly processes and larger samples remains necessary. In response to RQ2, the framework helps identify where AR guidance may be beneficial and where complementary interventions, such as practical training or simplified instructions, may be more appropriate.

5.3 Implications for Practitioners

The findings provide practical guidance for managers responsible for workforce training and AR implementation. Beyond the case study, the framework offers a structured approach for planning and evaluating AR interventions. As summarized in Table 2, managers can identify the capabilities required by each task, select relevant performance, quality, and wellbeing KPIs, and compare results with a predefined benchmark. The task-level classification can then distinguish

cognitive, operational, and combined difficulties, supporting decisions about AR implementation, content design, training, and process improvements.

First, the findings support selective AR implementation based on task characteristics and capability requirements. This is also relevant ergonomically, as the weight and dimensions of head-mounted displays may limit their suitability for continuous use throughout a work shift [4, 7–9]. Rather than deploying AR across the entire process, organizations can prioritize tasks involving technical documentation, information search, and component identification or positioning. AR may provide less support when execution depends strongly on experience-based capabilities such as *Manual Dexterity*. The framework can therefore help allocate AR resources according to task demands.

Second, the task-level classification provides a diagnostic tool for selecting suitable interventions. *High Cognitive Load* tasks may benefit from clearer visual guidance or additional contextual information, whereas *Operational Difficulty* tasks may require practical training, improved tools, or workstation redesign. *Critical* tasks may require combined interventions. Linking these categories to the capability framework helps managers determine whether performance gaps should be addressed through AR, conventional training, or process improvements.

Finally, the benchmark provides a reference for evaluating AR-assisted performance across individual tasks and the overall process. Depending on the application, it may be based on expert performance, production standards, historical data, or predefined targets. Organizations can therefore assess whether AR-assisted unskilled operators approach the selected benchmark across different task and capability profiles, rather than relying only on completion time or error counts. This comparison can guide AR content refinement, training resource allocation, and the identification of tasks requiring additional support.

Overall, the framework enables organizations to move from a general assessment of AR effectiveness to a task specific and capability-based evaluation. This is particularly relevant for manufacturers facing skilled labour shortages, as it supports targeted onboarding and upskilling while maintaining realistic expectations about AR. The framework therefore contributes to more evidence based and human centred implementation decisions in line with Industry 5.0 [38].

5.4 Limitations and future research

Despite the contributions of this study, several limitations should be acknowledged. The empirical application involved 13 employees from a single company, performing a fixed-sequence electrical-panel assembly in one experimental session. Moreover, the experimental design does not allow the independent effects of operator expertise and instructional medium to be disentangled, as experts used paper-based instructions while unskilled operators received AR guidance through Microsoft HoloLens 2. Consequently, the observed differences may reflect the combined influence of these factors rather than AR alone. The findings should therefore be interpreted as a task-level comparison between two operator–instruction configurations, rather than as causal evidence of AR effectiveness. Furthermore, the limited sample and single industrial setting constrain generalisability, while the case study demonstrates the applicability of the proposed framework without constituting its comprehensive validation.

The fixed sequence of predefined components and procedures also limited the assessment of certain worker capabilities. In particular, *Selective Attention* could not be comprehensively evaluated because participants were not required to identify relevant information among multiple alternatives. Furthermore, the CDI, ODI, and cognitive-demand threshold were derived from the

investigated sample and assembly process and may require calibration before application to other tasks, workforces, or production environments.

Future research should validate the framework across different assembly processes, industrial environments, and participant populations. Factorial experimental designs comparing expert and inexperienced operators using both paper-based and AR instructions would help isolate AR-specific effects. More dynamic assembly scenarios could enable a broader assessment of capabilities such as *Selective Attention*, while further studies should examine the stability of the CDI and ODI and establish procedures for calibrating the cognitive-demand threshold. Integrating physiological measures could provide additional indicators of cognitive and physical demands. Finally, future research could investigate adaptive AR guidance tailored to task requirements and individual worker capabilities.

6. Conclusions

This study contributes to the evaluation of AR-supported industrial assembly from conceptual, methodological, and empirical perspectives. Conceptually, it links worker capability requirements to AR-support mechanisms and cognitive and operational outcomes. Methodologically, the proposed framework distinguishes Understanding Time from Execution Time and evaluates operator–task observations against a reference benchmark, enabling a task-level assessment beyond aggregate performance measures. Empirically, the framework was applied to a 20-task electrical-panel assembly process, comparing AR-assisted unskilled operators with experts using conventional paper-based instructions.

The findings indicate that AR-assisted performance depends on the capability requirements of individual tasks. Contextual and sequential guidance appeared particularly valuable for interpreting unfamiliar instructions and executing procedural operations, whereas tasks requiring technical knowledge and experience-dependent manual capabilities remained more challenging. AR-assisted unskilled operators approached the expert benchmark in several demanding wiring tasks, although some positioning operations remained cognitively demanding despite relatively few execution errors. The task-level classification distinguished cognitive and operational difficulties, while the capability-based analysis helped explain the different performance patterns across assembly operations.

Overall, the proposed framework provides a structured basis for task-selective AR implementation and evaluation. By linking worker capabilities, performance-, quality-, and well-being-related KPIs, task-level classification, and benchmark-based comparison, it can help organizations identify where AR guidance may be valuable and where complementary training or process improvements may be needed. This capability-oriented approach supports more targeted and human-centered workforce training and AR deployment in industrial manufacturing.

7. Competing Interest

The authors have no relevant financial or non-financial interests to disclose.

8. Data Availability

Data will be made available on request.

9. Acknowledgement

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Appendix A

1. Why is it important to install covers on certain types of terminal blocks? (/1)

☐ To improve the appearance of the installation
☐ To prevent a short circuit
☐ To speed up the assembly process
☐ To identify the polarity

2. Which of these images shows a diode / resistor? (/1)



☐



☐



☐

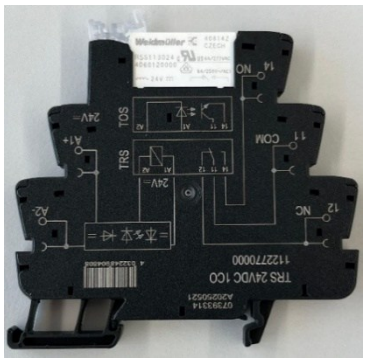
3. Where should the diodes / resistors be routed? (/1)

☐ Through the wiring duct
☐ Directly above the power supply
☐ Next to the fuse
☐ Under the DIN rail

4. In the image, mark the information you need to pay attention to. (/4)







5. Which component requires the most accurate positioning? (/1)

☐ The fuse
☐ The main switch
☐ The relay
☐ The terminal blocks

6. Which of these terminal blocks must be fastened to the DIN rail using a screwdriver? (/1)


☐


☐


☐

7. Why must this terminal block be fastened to the DIN rail using a screwdriver? (/1)

☐ To ensure greater mechanical stability
☐ To establish an electrical connection to the DIN rail as the protective earth (PE) conductor
☐ To increase the voltage
☐ To speed up the assembly process

Appendix B

Assembly Tasks

1. Main switch assembly
2. Contactor assembly
3. Terminal block assembly
4. Ground terminal block assembly WPE 6 and WPE 10
5. Electronic relay assembly WM112277
6. Relay 22K3 assembly
7. Circuit board assembly 20N1
8. Assembly of 2 x WSI6 terminal blocks with cover
9. Assembly of 2 x ZDU 4 terminal blocks
10. Assembly of 4 x AAAP12 2.5 terminal blocks with cover
11. Wiring of main switch and motor protection 1Q1 - 1Q2
12. Wiring of main switch and circuit breaker 1Q1 - 1F2
13. Wiring of motor protection and contactor 1Q2 - 20K1
14. Power supply wiring 10T1
15. Molex 3901-2240 wiring, part 1
16. Molex 3901-2240 wiring, part 2
17. Wiring of relay contactor 20K1 with circuit board 20N1-J13
18. Wiring of motor contactor 1Q2 with relay contactor 20K1 and circuit board 20N1-J18
19. Wiring of 2201 and 2202
20. Wiring of RL1, RL2, RL3 and RL4