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Assembly Complexity Index (ACI) for Modular Robotic Systems: Validation and Conceptual Framework for AR/VR-Assisted Assembly

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Abstract

The growing adoption of modular robotic systems presents new challenges in ensuring ease of assembly, deployment, and reconfiguration, especially for end-users with varying technical expertise. This study proposes and validates an Assembly Complexity Index (ACI) framework, combining subjective workload (NASA Task Load Index) and task complexity (Task Complexity Index) into a unified metric to quantify assembly difficulty. Twelve participants performed modular manipulator assembly tasks under supervised and unsupervised conditions, enabling evaluation of learning effects and assembly complexity dynamics. Statistical analyses, including Cronbach's alpha, correlation studies, and paired t-tests, demonstrated the framework's internal consistency, sensitivity to user learning, and ability to capture workload-performance trade-offs. Additionally, we propose an augmented reality (AR) and virtual reality (VR) integration workflow to further mitigate assembly complexity, offering real-time guidance and adaptive assistance. Sensitivity analysis confirms the robustness of the ACI under varying weighting schemes. The proposed framework not only supports design iteration and operator training but also provides a human-centered evaluation methodology applicable to modular robotics deployment in Industry 4.0 environments.

Keywords: assembly complexity index; modular robotics; human factors; task complexity index; Index; NASA TLX; AR/VR-assisted assembly; industry 4.0; design validation; learning curves; flexible manufacturing

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1. Introduction

With the increasing adoption of robotics and automation in industry, it has become evident that future factories will increasingly rely on robotic solutions. However, despite the wide availability of off-the-shelf manipulators, certain industries, particularly those dealing with lower payload capacities, remain hesitant to adopt such systems. For instance, the Food and Beverage sector contributed to only 3% of global annual installations of industrial robots, with no increase in installation rates compared to previous years [1]. Many commercial robotic systems are primarily optimized for heavy-duty, high-payload tasks, making them ill-suited for flexible, lightweight, or highly specialized applications. In addition to the mismatch of technical specifications, off-the-shelf manipulators often introduce operational challenges such as vendor lock-in [2], dependence on original equipment manufacturers (OEMs) for servicing, and substantial downtime during repairs or task reconfiguration [3]. These challenges are magnified when re-deployment is required to accommodate evolving shop-floor tasks, as fixed degrees-of-freedom (DoF), predefined workspaces, and rigid manipulator specifications create high costs associated with decommissioning, reconfiguration, and acquisition of replacement systems [4].

Task-agnostic, modular manipulator solutions therefore offer a highly attractive alternative. Research into modular robotic architectures has been ongoing since the early days of industrial robotics, with numerous approaches exploring unit-based reconfigurable designs. Historic developments include the Martonair Modular System [5], the Stuttgart Modular Robot [6], the Reconfigurable Modular Manipulator System [7], the Dynamically Reconfigurable Robotic System [8], Structural Modules [9], remote-actuation modular joints [10], and the Toshiba Modular Manipulator System, TOMMS [11]. While these early approaches demonstrated modularity principles, they were often limited by actuator weight and control system constraints due to the technological limitations of their time.

Contemporary research continues to refine modular robot designs, enabled by advances in lightweight motors, off-the-shelf electronics, integrated software interfaces, and modern manufacturing processes. In this context, the presented research focuses on the development of a modular manipulator that allows reconfiguration to meet bespoke end-user task requirements while remaining accessible to non-expert operators. A design-to-fit methodology was applied, leveraging Generative Design [12] and Additive Manufacturing [13] to optimize both structural design and manufacturing efficiency. The resulting system aims to minimize complexity across its lifecycle — from assembly and integration to deployment, operation, repair, and eventual disassembly — thereby enhancing accessibility, sustainability, and flexibility for end-users.

However, the technical design of a modular system is only part of the challenge. A critical consideration remains the cognitive and physical demands placed on operators during assembly and reconfiguration. While intrinsic system complexity may not always be reducible, evaluating subjective assembly complexity becomes essential to optimize user training, task allocation, and safety. Prior research indicates that operator performance often follows an inverted U-shaped curve, where excessive workload can impair accuracy and efficiency [14].

To address this challenge, this study introduces and validates a comprehensive Assembly Complexity Index (ACI) framework, combining the NASA Task Load Index (NASA-TLX) [15] and a customized Task Complexity Index (TCI) [16,17] into a unified evaluation model. This framework enables designers to quantify assembly complexity through both cognitive workload and task structure, supporting data-driven design iterations and effective user training strategies.

To validate the proposed ACI framework, an experimental study was conducted involving participants from both industry (PepsiCo) and academia (NTU Engineering). Participants performed supervised and unsupervised assembly tasks, providing workload and complexity ratings while also offering qualitative feedback to inform system improvements. Statistical analyses confirmed the framework's reliability, sensitivity to learning effects, and ability to capture how prior experience influences perceived complexity and task performance.

Building upon this foundation, the present study further proposes a conceptual integration of Augmented Reality (AR) and Virtual Reality (VR) technologies as an extension of the ACI framework. Emerging AR/VR tools have demonstrated considerable potential to support complex assembly tasks through immersive, adaptive guidance, potentially reducing both workload and task ambiguity for novice and expert operators alike. A conceptual AR/VR-assisted assembly workflow is introduced, outlining its prospective role in minimizing assembly complexity, accelerating learning, and enhancing operator safety within modular robotic deployment environments.

2. Materials and Methods

To rigorously assess the ease of assembly and the impact of design decisions or modifications on assembly complexity, it was essential to establish a systematic and quantifiable evaluation workflow. The proposed methodology integrates two established subjective assessment tools — the NASA Task Load Index (NASA-TLX) and the Task Complexity Index (TCI) — which were adapted for the context of modular robotic assembly. These tools collectively form the basis for calculating the Assembly Complexity Index (ACI), offering a comprehensive metric that captures both cognitive workload and perceived task difficulty.

2.1. NASA Task Load Index

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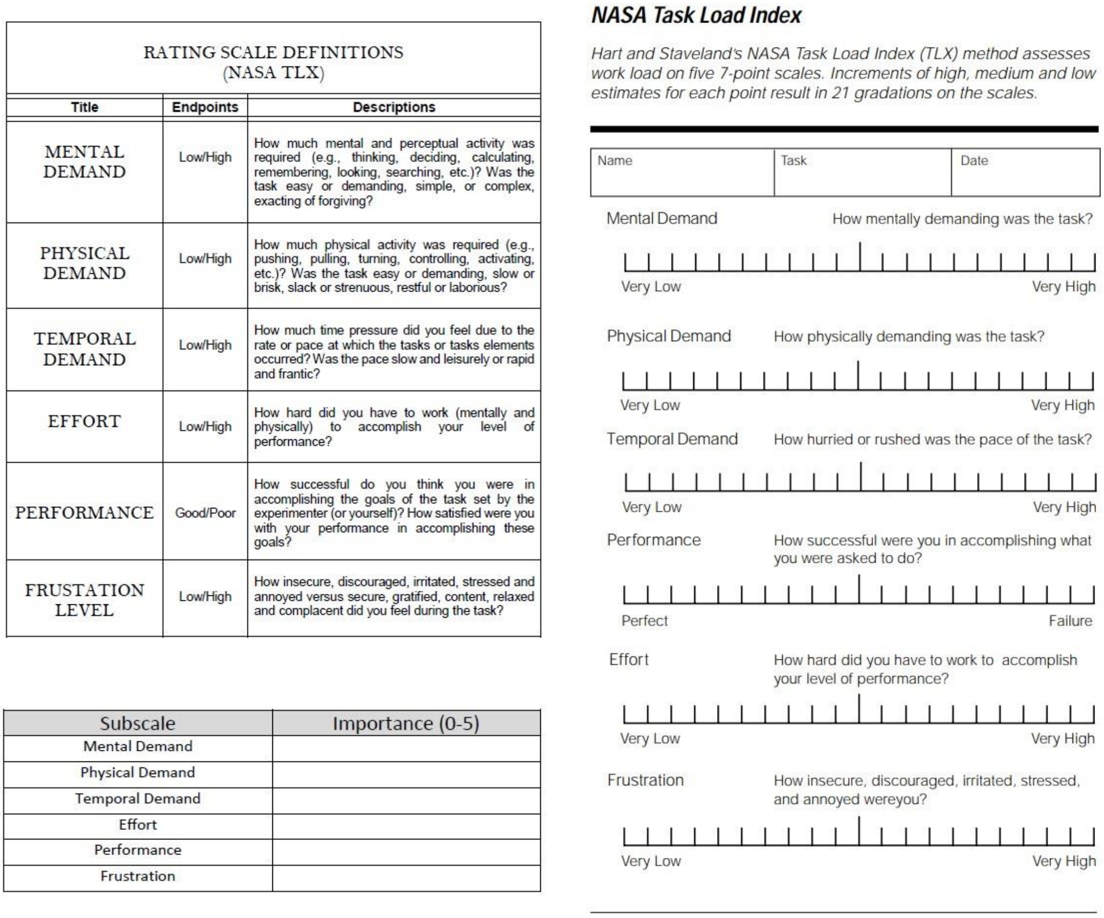
The NASA-TLX (as shown in Figure 1) is a widely recognized instrument for evaluating subjective workload [9] across six dimensions: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. Participants in this study rated each dimension on a 21-point scale, providing a granular view of the workload experienced during assembly tasks. The overall workload score for each participant (denoted as a_m) was calculated as a weighted average of the individual dimension scores:



RATING SCALE DEFINITIONS (NASA TLX)

Title	Endpoints	Descriptions
MENTAL DEMAND	Low/High	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple, or complex, exacting of forgiving?
PHYSICAL DEMAND	Low/High	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
TEMPORAL DEMAND	Low/High	How much time pressure did you feel due to the rate or pace at which the tasks or tasks elements occurred? Was the pace slow and leisurely or rapid and frantic?
EFFORT	Low/High	How hard did you have to work (mentally and physically) to accomplish your level of performance?
PERFORMANCE	Good/Poor	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?
FRUSTRATION LEVEL	Low/High	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Subscale	Importance (0-5)
Mental Demand	
Physical Demand	
Temporal Demand	
Effort	
Performance	
Frustration	

Figure 1. NASA Task Load index (NASA-TLX) Questionnaire.

$$a_m = \frac{\sum_{j=1}^{n} y_j * w_j}{\sum_{j=1}^{n} w_j} \qquad (1)$$

where y_j represents the rating for the j-th subscale, w_j is its assigned weight, m is the participant number and n is the number of subscales.

2.2. Task Complexity Index

To assess task complexity, a bespoke questionnaire (as shown in Figure 2) was developed based on prior work [16,17]. This instrument evaluates eight key complexity factors: root cause difficulties, information spread, ambiguity, coordination needs, guidance clarity, attention demand, safety-criticality, and temporal demand. Each factor was rated using a 7-point Likert scale, and the overall TCI score (b_n) was derived using the area ratio of an octagonal radar chart:

$$b_n = 7 \times \sqrt{\frac{\left(\sum_{i=1}^{n-1}\left(\frac{1}{2}x_i\, x_{i+1}\sin\left(\frac{\pi}{4}\right)\right)\right)+\frac{1}{2}x_n\, x_1\sin\left(\frac{\pi}{4}\right)}{\sum_{i=1}^{n+1}\left(\frac{7^2}{2}\sin\left(\frac{\pi}{4}\right)\right)}} \qquad (2)$$

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where x_i represents the transformed score for each complexity factor (8 - score for the nth indicator by the ith participant).

Task Complexity Questionnaire

Title	Description
Root Cause Difficulties	Were there any missing parts or tools that you think would have made the task easier?
Spread Of Information	Were you able to follow the instructions and complete the task?
Ambiguous Information	Was there any information missing?
Coordination	How difficult is the task to be performed by an individual?
Guidance Information	Were the instructions clear?
Attention Demand	How much importance would you give to the provided instructions? Was the task intuitive?
Severity / Safety	Did any safety concerns about the task hampered your performance and made the task more demanding?
Temporal Demand	Did the assigned time limit affected the task difficulty?

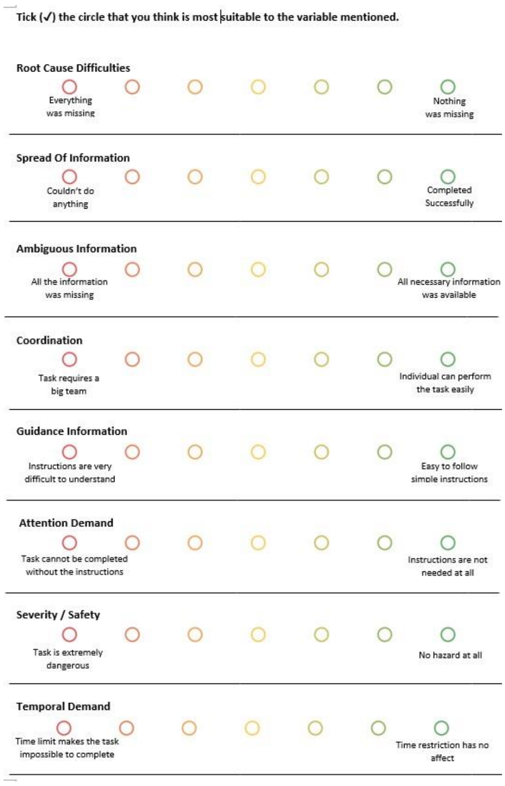
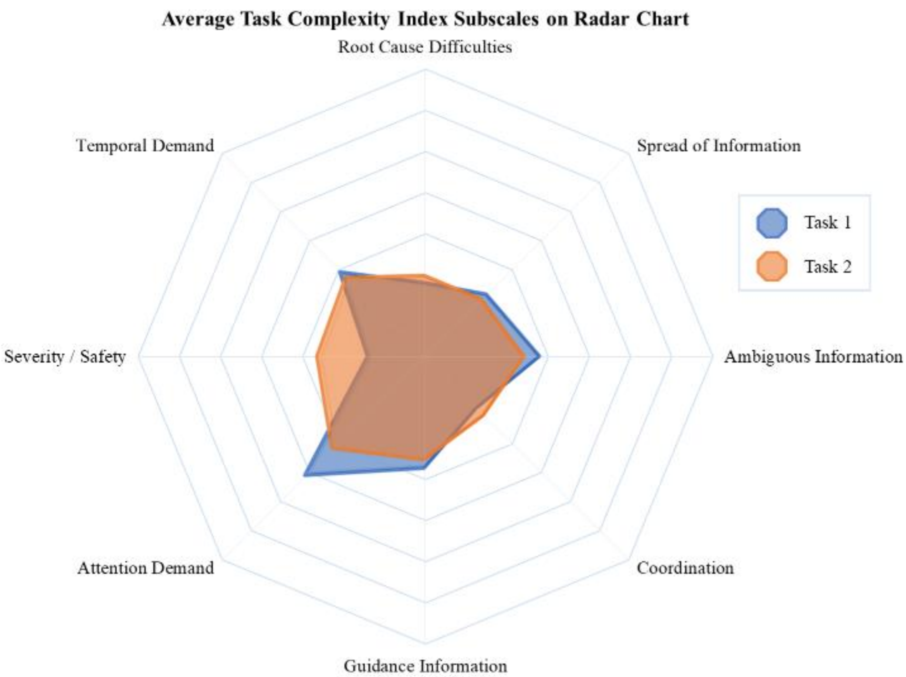


Figure 2. Bespoke Task Complexity Index (TCI) Questionnaire.

TCI involved the linearization of the area ratio plotted on an octagonal radar chart as shown in Figure 3.



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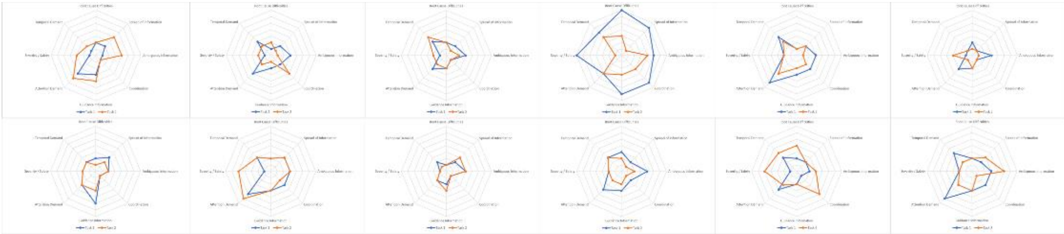

Figure 3. (Task Complexity Index) TCI Indicators on an Octagonal Radar Chart.

2.3. Data Normalization and Assembly Complexity Index

Both NASA-TLX and TCI values were normalized to a 5-point scale to ensure comparability:

$$\mathrm{a}'_m = \frac{5}{18.67}\mathrm{a}_m \quad (4)$$

$$b'_m = \frac{5}{7}b_m \quad (5)$$

where 18.67 and 7 represent the maximum achievable weighted scores for TLX and TCI, respectively.

The final Assembly Complexity Index (ACI, c_m) was computed as:

$$\mathrm{c}_m = \frac{\mathrm{a}'_m w_\mathrm{a} + b'_m w_b}{2} \quad (6)$$

where w_a and w_b are weights reflecting the relative importance of workload and complexity, normalized so $w_\mathrm{a} + w_b = 1$. These weights were determined by averaging participant input on the perceived importance score (Figure 4) of each dimension.

Figure 4. Normalised Weights for TLX and TCI.

2.4. Experimental Study

Twelve participants took part in two experimental sessions (Figure 5), each lasting approximately two hours, spaced two weeks apart. No prior information was provided about the specific assembly tasks.

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Figure 5. Some participants performing tasks during the Experimental Study.

- **Session 1 (Task 1)**: Participants were given up to 90 minutes to study an illustrated assembly manual and complete the assembly of a modular robotic joint, integrating 3D-printed structural parts, electronics, and standard tools. Success was defined by achieving functional joint control via a graphical interface.
- **Session 2 (Task 2)**: Participants assembled a 2-DoF manipulator configuration without access to the assembly manual or time constraints, using the same parts and tools.

After each task, participants completed the NASA-TLX and TCI assessments. Completion times were recorded, and TLX, TCI, and ACI scores were computed for each individual (Table 1).

Table 1. Summary of participant completion times and computed ACI components.

Candidate ID	Task 1				Task 2			
	Time (mins)	TCI (b'_m)	TLX (a'_m)	ACI (c_m)	Time (mins)	TCI (b'_m)	TLX (a'_m)	ACI (c_m)
1	46	1.36	0.50	0.34	47	2.22	1.04	0.64
2	70	1.52	2.02	0.96	58	1.26	3.09	1.36
3	73	1.45	1.91	0.91	61	1.43	1.34	0.68
4	66	4.07	1.18	0.88	57	1.96	1.66	0.86
5	76	1.18	0.64	0.38	62	0.94	1.20	0.57
6	65	2.08	2.32	1.14	60	1.49	1.95	0.93
7	67	1.75	3.14	1.43	53	1.43	3.23	1.44
8	83	1.99	2.93	1.37	72	2.47	3.80	1.77
9	58	1.21	1.16	0.59	61	1.34	1.39	0.69
10	66	2.00	2.79	1.31	68	1.34	3.00	1.33
11	37	1.45	1.04	0.56	51	2.47	2.12	1.10
12	56	2.17	3.02	1.42	50	1.82	3.21	1.47

2.5 AR/VR Integration: Conceptual Framework for Future Deployment

To further reduce assembly complexity, particularly for novice operators, this study proposes an **Augmented Reality (AR)** and **Virtual Reality (VR)** extension to the ACI framework. These technologies can provide immersive, adaptive guidance, enhancing assembly accuracy, reducing workload, and accelerating skill acquisition [18,19].

2.5.1. AR/VR Workflow for Assembly Assistance

The envisioned workflow incorporates AR/VR at key decision and execution points:

1. **User Assessment-**Identify the operator's skill level through self-reporting or automated detection (e.g., prior experience, task history).
2. **Initial ACI Estimation-**Estimate task complexity based on system configuration and user profile.
3. **AR/VR Trigger Condition-**If estimated ACI exceeds a defined threshold, activate AR or VR assistance.
4. **AR Assembly Guidance-**AR headsets (e.g., HoloLens, Magic Leap) overlay part placement, alignment cues, fastener types, and sequence instructions directly onto the physical workspace [20,21].
5. **Optional VR Pre-Training-**VR environments simulate the assembly task, allowing users to practice steps virtually before attempting physical assembly [22].
6. **Real-Time Monitoring and Feedback-**Dynamic ACI estimation adjusts as the user progresses, providing adaptive assistance (e.g., highlighting missed steps, correcting errors) [23].

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7. **Post-Assembly Validation-**Completion of assembly is verified against digital twin models; performance data are stored for training refinement [24].

2.5.2. Visual Concept of AR/VR Workflow

The proposed AR/VR-enhanced assembly process as illustrated in Subsection 3.5.1 and Figure 6, which presents a flowchart detailing the decision points and stages of the assisted assembly workflow. The diagram highlights how operator assessment and initial ACI estimation determine whether immersive assistance is activated. The workflow integrates AR overlays for real-time assembly guidance and VR environments for pre-task simulation, both feeding into dynamic ACI monitoring and post-task validation.

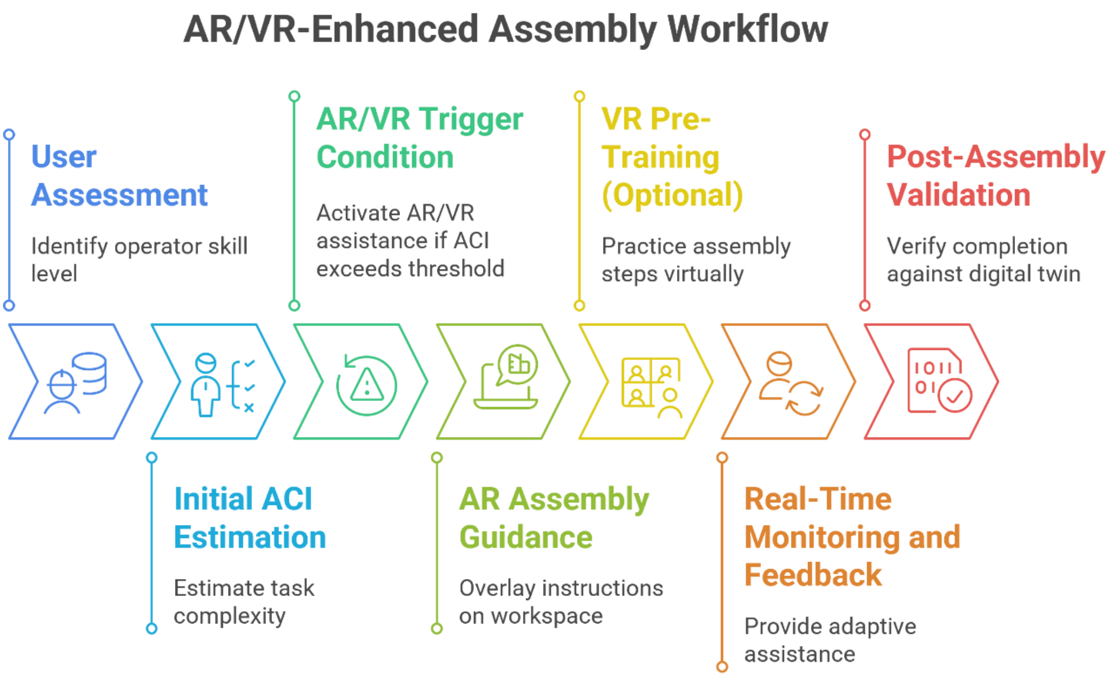

Figure 6. Conceptual flowchart of the AR/VR-assisted assembly workflow showing user assessment, ACI estimation, AR/VR activation, interactive guidance, and feedback loop.

To provide a clearer vision of how AR would assist the operator during assembly, Figure 7 depicts a hypothetical view through an AR headset. The visual overlay includes part alignment indicators (e.g., highlighted in green when correctly positioned), overlay in orange if part not in correct place, white for the final position for successful assembly, and arrows showing the sequence of operations. This contextual, real-time guidance aims to reduce ambiguity, consolidate instruction delivery, and minimize attention demand by bringing critical information directly into the user's field of view [19].

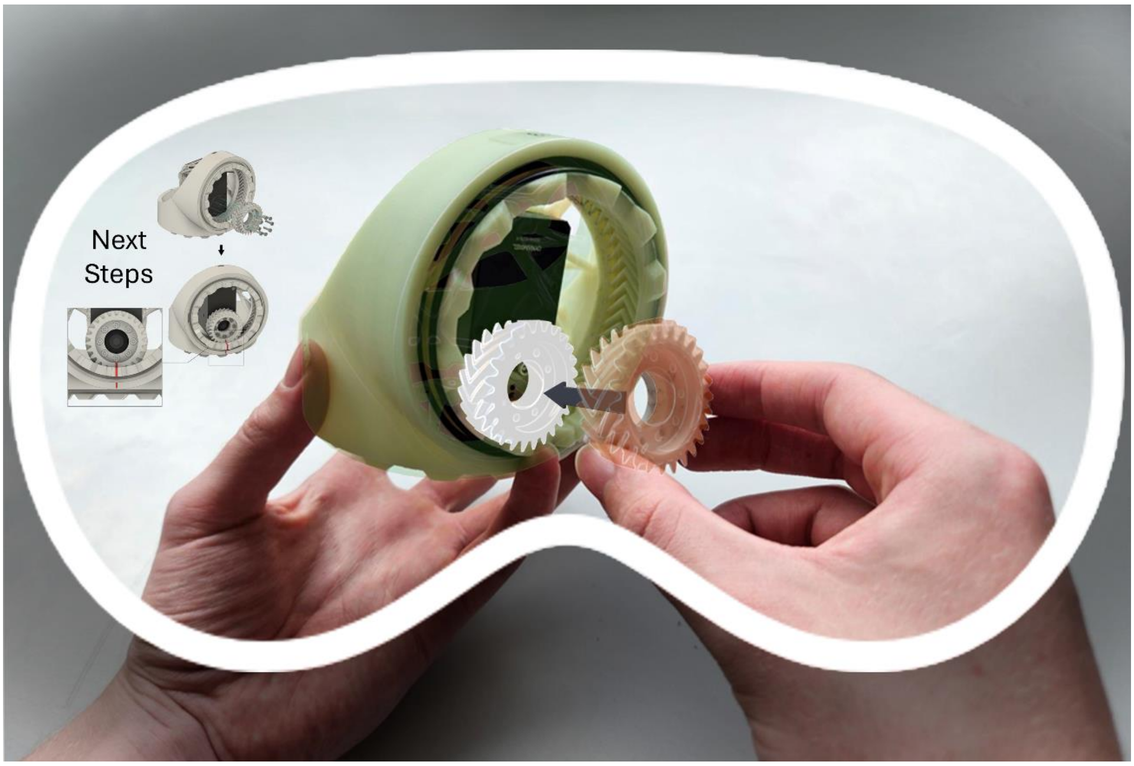

Figure 7. Example AR headset view mock-up illustrating real-time visual overlays for part alignment and task sequence cues during assembly of a modular joint.

Additionally, Figure 8 shows a conceptual snapshot of a VR training environment designed to familiarize users with the assembly task before engaging with physical components. The virtual environment provides exploded views of the modular robotic joint, allowing users to interactively practice assembly steps, identify components, and understand the sequence of operations without material costs or assembly risks [22,25].

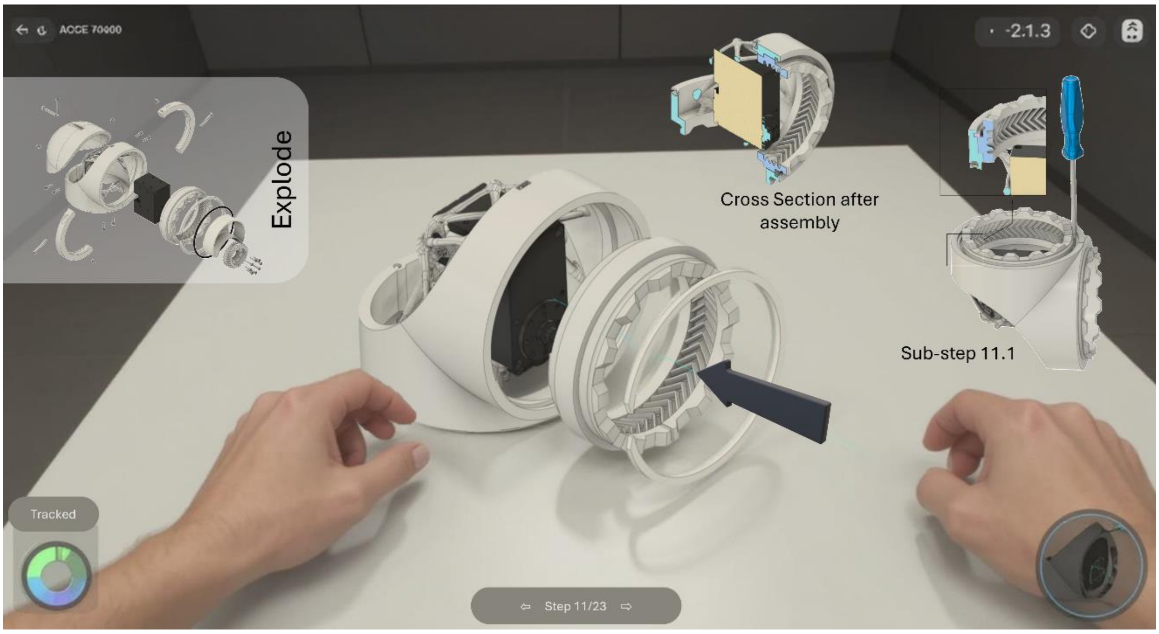

Figure 8. Example VR training interface screenshot depicting assembly steps of the modular joint (Patent Published: WO2025040883) with interactive part selection and step-by-step assembly simulation.

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Together, these figures illustrate how AR and VR can be seamlessly integrated into the ACI methodology, providing immersive, adaptive support to minimize complexity and improve assembly outcomes.

This conceptual framework provides a foundation for integrating AR/VR into the ACI methodology. Future experimental validation will quantify the actual reductions in workload and complexity achievable through these technologies, helping to refine both hardware requirements and software interfaces for modular robot assembly in industrial settings [23,24].

3. Results

This section presents the outcomes of the experimental study, combining both statistical analysis and observational insights to evaluate the Assembly Complexity Index (ACI) and its components across two robotic assembly tasks.

3.1. Internal Consistency and Reliability

To assess the reliability of participant ratings, Cronbach's alpha was computed for both the Task Complexity Index (TCI) and the NASA Task Load Index (TLX).

- **TCI** showed acceptable internal consistency with alpha values of 0.707 (Task 1) and 0.724 (Task 2), consistent with thresholds for moderate reliability (Murphy and Davidshofer, 1994).
- **TLX** demonstrated strong reliability with alpha values of 0.831 (Task 1) and 0.777 (Task 2), validating the use of this workload scale in assembly assessment.

3.1. Statistical Analysis

- **Completion time:** Mean completion time for Task 1 was 62 minutes (SD = 14), while Task 2 averaged 58 minutes (SD = 9), despite Task 2's higher complexity. A paired t-test indicated that Task 2 was completed significantly faster ($p = 0.026$), suggesting a positive learning effect from the first task.
- **TCI and TLX correlations:** In Task 1, TLX showed a moderate positive correlation with completion time ($r = 0.40$), indicating that higher workload perception was associated with longer task duration. TCI correlation with time was weaker ($r = 0.13$). In Task 2, TCI and time showed a mild negative correlation ($r = –0.22$), suggesting that participants perceiving higher complexity did not necessarily take longer, possibly due to prior exposure to assembly steps.
- **ACI progression:** The ACI increased in Task 2 ($p = 0.046$), driven primarily by elevated workload ratings, even though task completion time decreased. This reflects the cognitive demands of assembling without instructions, despite procedural familiarity.
- **Internal consistency:** Cronbach's alpha for TCI was acceptable at 0.71 (Task 1) and 0.72 (Task 2); for TLX, alpha was 0.83 (Task 1) and 0.78 (Task 2), confirming reliable participant responses.

3.3. Observational Findings

Qualitative observations revealed that while participants generally found the physical manipulation of parts intuitive, challenges arose in identifying the correct assembly sequence and the type of fasteners required — especially in Task 2 where no manual was provided. Participants expressed a strong preference for visual aids and more guided feedback, reinforcing the potential of integrating immersive technologies such as AR and VR for real-time, context-sensitive instruction.

Some participants noted that although Task 2 was technically more complex, they completed it faster because of familiarity with subassemblies, indicating that procedural memory can compensate for missing external guidance. These findings highlight the need for adaptable support systems that respond dynamically to user expertise and evolving task conditions.

4. Discussion and Conclusion

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This study presented and validated a human-centred Assembly Complexity Index (ACI) framework for evaluating modular robotic system assembly tasks. The integration of NASA-TLX and Task Complexity Index (TCI) provided a comprehensive means to quantify both cognitive workload and perceived task complexity, supporting data-driven design decisions and operator training strategies.

4.1. Learning and ACI Dynamics

The results revealed clear evidence of learning effects: participants completed the more complex Task 2 faster than Task 1, despite reporting higher workload. This suggests that early exposure to assembly steps contributes to procedural knowledge, which helps offset cognitive demands in subsequent tasks. However, the elevated ACI in Task 2 illustrates that perceived workload remains an important factor, even when task familiarity increases. This underscores the value of supporting operators not only through design simplification but also through enhanced training and guidance mechanisms.

4.2. AR/VR as a Future Integration Pathway

The conceptual AR/VR integration proposed in the methodology aims to address these residual cognitive challenges. Building on the foundational Assembly Complexity Index framework developed in previous work [26], the current expansion proposes immersive real-time visual overlays, interactive prompts, and pre-task simulations. These AR/VR technologies have the potential to reduce ambiguity, consolidate information delivery, and lower attention demand — key contributors to elevated ACI scores. Although the current work did not experimentally validate AR/VR assistance, the workflow outlined provides a foundation for future studies. These studies will aim to quantify the impact of immersive guidance on ACI components, assembly time, error rates, and user satisfaction.

4.3. Implications for Modular Robotics Deployment

The ACI framework, particularly when extended with AR/VR support, offers a versatile tool for managing human factors in the deployment of modular robotic systems. Applications include operator onboarding, maintenance and repair training, and the safe reconfiguration of manipulators on dynamic shop floors. The framework's adaptability to different levels of system complexity and operator expertise makes it well suited for Industry 4.0 manufacturing environments.

4.4. Limitations and Future Work

While the present study provides strong initial validation of the ACI model, limitations include the relatively small sample size and the focus on a single manipulator type. Future work will extend testing to diverse modular configurations, different user populations, and real industrial settings. Experimental validation of AR/VR assistance will form a key next step, as will longitudinal studies examining how ACI evolves with repeated exposure and skill development.

5. Patents

The modular joint designs illustrated in the AR/VR conceptual mockup figures are the original intellectual property of the corresponding author and are protected under the following published patent:

- WO2025040883: Modular Robotic Joint Assembly and Method of Use

This patent covers the generatively designed housing, integration of internal herringbone gear systems, and modular connection architecture depicted in the assembly sequences and visual overlays used in this study.

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Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACI	Assembly Complexity Index
AM	Additive Manufacturing
AR	Augmented Reality
CAD	Computer-Aided Design
DoF	Degrees of Freedom
GD	Generative Design
GUI	Graphical User Interface
NASA-TLX	NASA Task Load Index
OEM	Original Equipment Manufacturer
TCI	Task Complexity Index
TLX	Task Load Index
VR	Virtual Reality

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