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The user experience in industrial human-robot interaction: A comparative analysis of Unimodal and Multimodal interfaces for disassembly tasks

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ABSTRACT

In the Industry 5.0 context, ensuring effective Human-Robot Interaction (HRI) is key to supporting human involvement in production processes. Interfaces are the foundation of this collaboration and serve as vital communication channels which bridge the gap between users and robotic systems. This study compares unimodal and multimodal interfaces and their impact on user experience (UX) in an HRI context. Unimodal interfaces, while simplifying implementation, may restrict the richness of communication, while multimodal interfaces provide detailed and flexible interaction, enhancing the conveyance of complex information. However, designing effective multimodal interfaces presents challenges due to their inherent complexity in managing multiple modalities. This paper presents an HRI disassembly case study comparing the impact of these interfaces on the UX. A methodological approach was used to monitor operator performance, physiological responses, and perceptual responses. An electroencephalogram was employed to objectively record the operators' emotional responses of operators without interrupting or hindering the process. Twenty participants (10 men and 10 women) were involved in the study. The results indicate that levels of memorization and mental workload are lower when using the multimodal interface, a finding consistent across men and women. These findings suggest that the multimodal interface is an appropriate choice, not only for reducing memorization and mental workload levels, but also for its inclusive approach. This aligns with the objectives of Industry 5.0, promoting the development of technology that meets diverse user preferences and abilities, thereby ensuring greater accessibility and a more user-centric technological landscape.

1. Introduction

The increasingly prevalent integration of robotic systems into industrial environments [1–4] has given rise to the need for collaborative efforts between humans and robots. This symbiotic relationship assists human workers by entrusting robots with hazardous and physically demanding responsibilities [5]. For this partnership to be successful, users must view the robot as a valuable collaborator.

The European Commission's [6] recent approach to advanced industrial systems places a strong emphasis on prioritizing the well-being of workers involved in the production process. Industrial Human-Robot Interaction (HRI) aims to harness the distinctive capabilities of both robots and humans, facilitating a secure and mutually beneficial sharing of tasks in a boundary-less, collaborative workspace [7]. This configuration encourages close and safe interaction between humans and robots, effectively harnessing the strengths of each.

Robots require user interfaces (UI) to interact with humans and these serve as the main communication channel between the two. High-quality HRI demands intuitive interfaces to allow operators effortlessly input instructions and receive clear information. However, robots are perceived differently by humans than other technologies [8], necessitating unique acceptance models. In recognition of this fact, the Human-Robot Collaboration Acceptance Model (HRCAM) extends beyond technical functionality to incorporate human factors and experiences, especially in industrial settings. The HRCAM underscores the intricate interplay of factors influencing HRI, addressing unique challenges and expectations.

User Experience (UX) plays a crucial role as the primary connection between individuals and robots. Based on ISO 9241–210 [9], UX is defined as 'a person's perceptions and responses resulting from the use or expected use of a product, system, or service.' This encompasses user emotions, beliefs, preferences, perceptions, physical and psychological

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responses, behaviors, and accomplishments that occur prior to, during, and after usage. In this vein, Marvel et al. [1] outlined two key criteria to move from the traditional paradigm of manufacturing robotics to a new generation of user-friendly designs in HRI: (i) demonstrate that human-centered designs are indeed more effective and/or efficient; and (ii) verify that operator response to the technology is positive. This involves defining the intended interactions between humans and robots and the purpose of information exchanges, which are largely influenced by the scope of application and the distinct roles of humans and robots.

In light of the technological innovations shaping the way humans work alongside robots in industry, gaining a greater understanding of the interfaces which facilitate human-robot communication is critical. These interfaces are the key to enhancing collaboration and productivity between humans and robots. According to Prati et al. [10], the type HRI selected for any given task is related to the level of interaction required. Specifically, the first level of interaction (coexistence) is usually satisfied with graphical interfaces. The second level of interaction (cooperation) frequently requires more advanced interfaces, such as voice and gestures. Finally, the third level of interaction (collaboration) may also require direct physical or haptic interaction to be effective and natural at the same time.

X. V. Wang et al. [11] analyzed the relationship between interaction and risk, finding that as the level of interaction increases, so does the associated risk, especially in close human-robot collaboration scenarios, where safety is of utmost importance. In the case of human-robot coexistence, the engagement and interaction complexity are low, and safety is relatively easy to ensure due to the presence of physical boundaries that protect the operator. In the cooperation mode, both the interaction and safety risk increase significantly due to greater direct contact between the human operator and the robot. However, fully symbiotic collaboration between the human and the robot implies that both parties perform the task collaboratively, inevitably involving direct contact between the human operator and the robot, and a higher level of safety risk (Fig. 1).

The visual representation in Fig. 1 categorizes the types of interfaces and corresponding safety levels across different HRI stages:

- Coexistence: The base level, depicted by the pink parallelogram, primarily uses graphical interfaces designed for minimal interaction where safety is relatively easy to ensure due to minimal direct contact between humans and robots.
- Cooperation: This level involves more advanced interfaces such as voice and gesture (orange and blue parallelogram). Increased direct interactions at this stage require enhanced safety measures.
- Collaboration: Represented by the green parallelogram, the highest level of interaction may incorporate haptic interfaces, thus becoming multimodal with the potential to include various modes of interaction. This level demands the most stringent safety protocols to manage the inherent risks associated with close human-robot collaboration.

Human-robot communication interfaces can be unimodal, focusing on a single method of communication, or multimodal, combining various methods for richer interaction. Unimodal interfaces offer simplicity but may limit adaptability, while multimodal interfaces provide flexibility. The choice between unimodal and multimodal interfaces is contingent on factors such as the nature of the task, the abilities of the user, and the desired efficiency of interaction. Multimodal interfaces are more effective for conveying complex information, while unimodal interfaces facilitate greater ease of use. To achieve optimal HRI, it is important to understand the interactions between various communication methods and their effect on UX and human factors.

This study conducts a comparative analysis of multimodal and unimodal interfaces to evaluate their impact on HRI and the emotional responses of human operators. By understanding how these interfaces influence interaction quality and UX, this research aims to take a step toward identifying optimal communication strategies that enhance the efficiency, safety, and satisfaction of industrial workers. These insights will help design user-friendly HRI systems that can better support human operators, improve collaborative performance, and foster positive attitudes toward robotic co-workers in industrial environments.

1.1. *Research motivation and hypothesis*

This study compares the impact of multimodal and unimodal

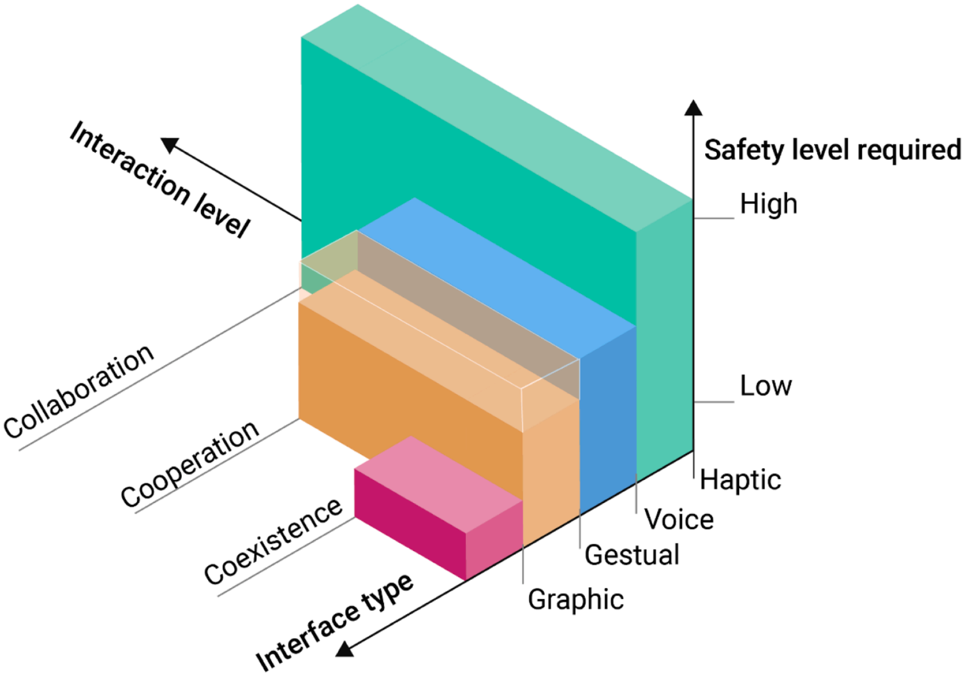


Fig. 1. HRI Levels, Interface Types, and Corresponding Safety Levels.

interfaces on a spectrum of human responses. Our research focusses on the performance of human-robot teams engaged in disassembly tasks, as well as the physiological and perceptual user responses to each type of interface. These responses encompassed aspects such as engagement, memorization, emotional valence, and mental workload. The HUROX questionnaire [12] was also employed to measure perceptual factors including usefulness, ease of use, safety, controllability, learnability, attitude, intention to use, and satisfaction.

Given the increasing integration of collaborative robots in industrial settings a key research question arises:

How do unimodal and multimodal interfaces influence memorization, mental workload, engagement, emotional valence and perceived UX in an industrial HRI context?

To address this question, the following hypothesis was formulated:

In the context of HRI in an industrial environment, using multimodal interfaces leads to a decrease in memorization values and mental workload, increase of engagement and emotional valence, together with a perceived improvement in UX when compared to using a unimodal interface.

To ensure a comprehensive analysis, we designed and implemented an experimental setup comprising three main facets according to the previously developed experimental protocol for manufacturing contexts [13]:

i) **Performance Indicators:** To evaluate the progression of human-robot team performance in disassembly tasks.
ii) **Physiological Responses:** Electroencephalogram (EEG) data was collected to quantify user engagement, memorization, emotional valence, and mental workload during the interaction.
iii) **Perceptual Responses:** The HUROX questionnaire was employed to assess UX, including variables such as perceived usefulness, perceived ease of use, perceived safety, controllability, learnability, attitude and intention to use, and satisfaction [12].

2. Research background

Efficient collaboration between industrial workers and robots is fundamentally reliant on the sophistication of the interfaces that facilitate their interaction. Advanced interfaces are essential not only for delivering clear communication [10], but also for enhancing the UX. They play a critical role in helping users understand robot behaviors and respond appropriately in dynamic situations [14], which is crucial for maintaining operational efficiency and safety. Furthermore, the intuitiveness of these interfaces and the quality of the feedback they provide are central to ensuring safety in HRI [15].

2.1. Impact of interfaces on HRI

Interfaces play a crucial role in HRI by facilitating effective communication and information exchange. They are defined as the means by which hardware and software connect to establish communication between humans and systems [16]. The integration of inputs from different modalities allows stimuli from one sensory modality to influence how stimuli from another modality are processed and remembered [17].

Purely visual interfaces have proven effective for continuous supervision and the simultaneous management of multiple robots. Their ability to provide detailed visualization of the operational parameters and work environment of the robot is essential for maintaining efficiency and safety in industrial operations [18,19] Combining visual and auditory information creates a multimodal interface that can enhance user perception and response. Auditory signals can provide immediate alerts, reinforce visual information, and facilitate divided attention, which is particularly useful in dynamic industrial environments where operators need to manage multiple tasks [17].

Analyzing the difference between purely visual interfaces and those that incorporate auditory components is essential for optimizing HRI systems. The literature suggests that multimodal interfaces can improve operational efficiency and reduce user cognitive load. There is robust behavioral evidence confirming that a range of visual processes—including detection, identification, and localization—can be facilitated by the concurrent processing of auditory stimuli [17]. A study by Murphy et al. [20] demonstrated that operators using multimodal interfaces could process information more quickly and with fewer errors than those using purely visual interfaces. Dragan et al. [21] found that interfaces combining visual and auditory information allow for better decision-making in teleoperation scenarios. Additionally, Villani et al. [15] highlighted that the addition of auditory signals can enhance safety by providing rapid alerts that help operators react more quickly to hazardous situations.

However, none of these studies have employed physiological devices to evaluate whether this evidence holds true. This gap in the literature presents an opportunity for further research with advanced physiological monitoring techniques, such as electroencephalography (EEG), to obtain objective measurements of operator cognitive load when using different types of interfaces.

2.2. Assessment of human factors in HRI manufacturing tasks

The assessment of human factors in HRI is gaining significance in light of the European Commission's introduction of Industry 5.0, which prioritizes the wellbeing of humans. A recent review of the literature has identified several studies highlighting the importance of a human-centered approach in evaluating HRI [22]. Table 1 summarizes 11 case studies from 2013 to 2023, categorizing evaluation metrics into performance, physiological, and perceptual indicators.

The table shows that in terms of performance indicators, the most employed metric is task execution time [22]. Other metrics, such as robot idle time and the distance between the robot and the human, are also utilized. Ultimately, the key consideration in this context is that the selected performance indicator should effectively reflect the extent to which the interaction between the individual and the robot collectively fulfils and meets the desired objective, whether it pertains to assembly, disassembly, or any form of industrial operation.

Physiological assessment has not been extensively employed in many experimental studies thus far, although there is a discernible trend in recent years towards its greater implementation. This can be attributed to technological advancements, in which physiological devices have become progressively more precise and less intrusive [23]. They identified that the EEG being the most used [23]. Nevertheless, no case studies in the review were from the HRI context [22]—possibly due to the complexity of using such devices in environments requiring greater user mobility—. This presents an exciting research opportunity to leverage the dominant modality in UX studies for advancing HRI research. In this study, we include physiological monitoring as an innovative method to objectively evaluate human factors, thereby minimizing retrospective bias. This is in line with previous studies [22, 23] that highlighted the significance of integrating monitoring techniques in human factor assessments for more accurate evaluations and reduced bias.

Typically, brain activity is recorded using EEG, which captures electrical brain activity through scalp electrodes placed in standard positions [24]. Each electrode records the voltage from neuronal activity in its specific brain region. Brain activity has been linked to various emotions such as emotional Valence [25–27], Memorization [28–31], Mental Workload [32–35], and Engagement [36–38], demonstrating the utility of EEG in evaluating cognitive and affective responses during HRI.

The utilization of questionnaires is prevalent in this genre of research, which may stem from their role as quantitative indicators of individual perceptions. However, despite their widespread use, there is a conspicuous absence of questionnaires specifically tailored to the

Table 1
Articles employing an experimental approach to analyze the human factor in HRI environments.

Ref.	Objective	Task	Evaluation methods		
			Performance indicators	Physiological device	Perceptual indicators
[43]	Demonstrate enhanced robot setup time and performance, especially for inexperienced operators, with a flexible interface.	Pick and place Configurable packaging	Task execution time Simultaneous movement Average separation distance Robot idle time Person idle time	No	Open-ended questions about trust in automation. Interview with questions adapted from WAI Site Usability Testing Questions about impressions of the current UI and operation of the robotic cell. Flow Conditions Questionnaire
[44]	Examine human response to motion-level robot adaptation.	Assembly	Task execution time Simultaneous movement Average separation distance Robot idle time Person idle time	No	Questionnaire (Satisfaction with the robot as a companion; and perceived safety and comfort)
[45]	Assess the efficacy of Augmented Reality Instructions in HRC.	Assembly	No	No	SUS Questionnaire General Interest Questionnaire
[46]	Evaluate the effect of immersive technologies on teleoperation spatial perception.	Touch Pick and place Path following	Task execution time Errors Accuracy of path-following	No	IBM Computer Usability Satisfaction Questionnaire Questionnaire based on the presence questions [47,48]
[49]	Evaluate performance, safety and ergonomics of their specific model.	Assembly	Task execution time Robot idle time	No	Self-generated questionnaire to assess UX addressing safety, information processing, ergonomics, autonomy, competence, and affinity
[50]	Analyze the effect of motion planning parameters on human factors in HRI.	Disassembly Pick and place	Task execution time Average separation distance. Ratio of the time required to complete the task with and without the robot	No	Self-generated questionnaire on perceived danger-safety
[5]	Assess musculoskeletal risk, wellbeing and acceptance of robots associated with the pre-assembly position before and after the implementation of HRC control.	Assembly	Task execution time Variability in production times Production rate	No	Questionnaire to assess worker perceptions of robots in industry and associated ergonomic improvements
[51]	Analyze the effect of assembly scenarios in workload and operator behavior.	Assembly	No	No	System Acceptance Scale NASA-TLX Single item to assess: Frustration Single item to assess: Perceived Enjoyment Short Stress State Questionnaire (SSSQ) Trust in HRC questionnaire SUS questionnaire
[52]	Assess the relationships between HRC speed, distance and control, perceived interaction quality, affective state, and stress.	Assembly	Task execution time Robot speed Distance between person and robot.	Skin Conductance Response (SCR) HRV	NARS Questionnaire Quality of Interaction Questionnaire SAM
[53]	Assess the evolution of operator well-being and performance evolve during continuous interaction with a collaborative robot in repetitive assembly.	Assembly	Number and type of process failures	HRV EDA	No
[54]	Explore disparities between manual and automated repetitive assembly processes.	Assembly	No	HRV EDA	NASA-TLX SAM
[55]	Assess the relationship between cognitive workload, workstation design, user acceptance, and trust	Assembly	No	No	NASA-TLX Acceptance Scale SUS SSQ Trust in HRI

intricacies of HRI. Bröhl et al. [4] emphasized that robots are fundamentally perceived differently from other technologies, leading individuals to harbor distinct expectations. The only standardized questionnaire identified to be explicitly designed for robots, the Trust in HRI [39], falls short in comprehensively capturing the UX. Furthermore, the recurrent use of various self-generated questionnaires highlights the development and implementation of instruments purposefully crafted for HRI assessment. Importantly, the adoption of multiple questionnaires to gauge specific human factors not only introduces the inconvenience of multiple tools but also compromises the holistic perspective.

The Table 1 also reveals that only one study focused on a disassembly task. In the field of HRI, effective treatment of end-of-life (EoL) products involves remanufacturing, which requires the disassembly of products. Although industrial robots automate these tasks, they are not always able to manage uncertainties related to EoL products and the intricate nature of disassembly. HRI offers a solution by combining collaborative robots and human workers, nonetheless, challenges persist in optimizing their interaction, impacting productivity and safety. While several studies focus on the development of HRI assembly environments [40–42], the current literature lacks human-centered evaluations specifically tailored to the disassembly process in HRI manufacturing. Addressing this gap is critical for advancing the understanding and optimization of HRI in manufacturing disassembly.

To date, a limited number of studies have employed an experimental approach to investigate the impact of HRI interfaces on engagement, memorization, valence, mental workload, and the overall perception of the UX, utilizing performance indicators, physiological devices, and gathering UX perceptions. Therefore, in this work we compare the influence of multimodal and unimodal interfaces on human factors. Specifically, we designed a disassembly task simulating the process of taking apart a refrigerator, where participants interacted with either a unimodal (visual) or a multimodal (visual and voice) interface. The task involved two main objectives: disassembling a joint and handling electronic components in a step-by-step process. During the task, we employed an EEG to objectively record the participants' emotional responses. Additionally, we gathered their perceptions through a specifically developed questionnaire to assess UX in industrial HRI, the HUROX [12].

3. Research methodology

To compare the influence of multimodal and unimodal interfaces on human factors we used a multi-method and human-centered approach, considering data of a diverse nature.

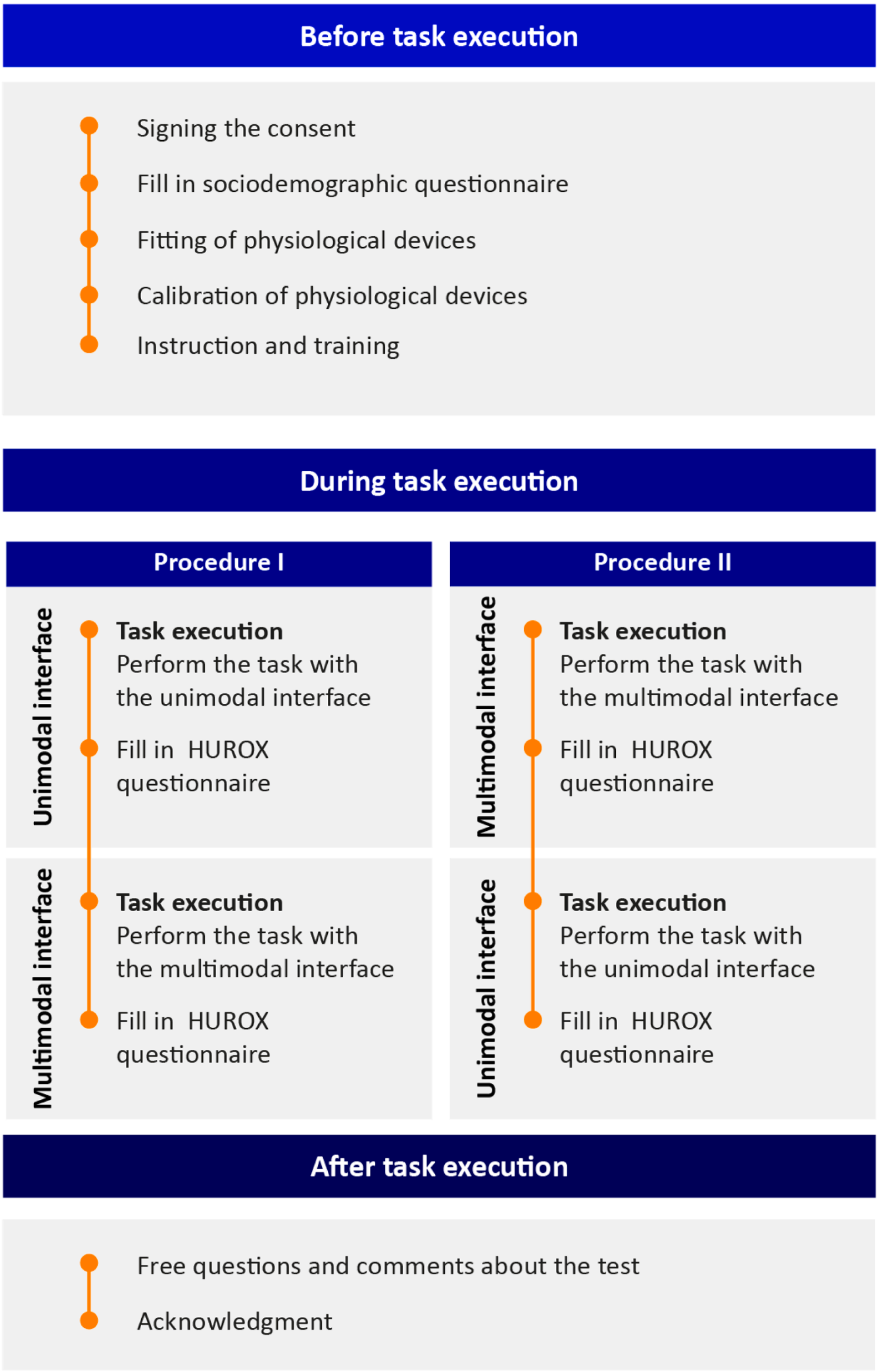


Fig. 2. Experimental procedure.

3.1. Experimental procedure

The study was divided into three phases (Fig. 2), in accordance with the protocol proposed [13]: (1) pre-task execution phase, (2) during task execution phase, and (3) post-task execution phase.

3.1.1. Pre-task execution phase

The pre-task execution phase consisted of five steps:

Step 1 - Sign consent form: At the beginning of the study participants were asked to sign a form to confirm their informed consent. This form detailed the test procedures, the data collection involved, and their rights as participants.

Step 2 - Sociodemographic questionnaire: Participants were then asked to complete a socio-demographic questionnaire, which required their age, gender, and any prior experience with robots. Participants selected the statement that best described their level of prior experience, as presented in Table 2.

Step 3 - Fit physiological devices: Participants were equipped with an EEG headset—specifically the Diadem de Bitbrain [56], detailed in section 3.5.2. Physiological indicators.

Step 4 – Calibrate physiological device: The device was calibrated in accordance with the procedure outlined by the developer [57]. The specific steps undertaken were:

- Familiarization: Participants were exposed to stimuli to acquaint them with the test content and the overall protocol. Familiarization blocks are not subject to analysis, and no data was collected during this phase. Participants were briefed on the task and its nature.
- Washout 1: Participants were directed to close their eyes and adopt a resting state. The washout block aims to disassociate emotional responses from one block to the next and establish a null baseline for EEG.
- Eyes Open: Participants were instructed to enter a resting state with their eyes open, serving as a baseline measurement.
- Calibration: Built-in stimuli were presented to each participant to determine the range of individual physiological responses and standardize the responses across all participants.
- Washout 2: Participants were again instructed to close their eyes and enter a resting state.

Step 5 - Instruction and training: The participants were instructed as regards their responsibilities and task-specific training was conducted to ensure their understanding of the assigned duties.

3.1.2. During the task execution phase

To mitigate potential biases introduced by the order of interface use, two distinct procedures were implemented, ensuring that task learnability did not unduly influence the results. In the task execution phase, we explored the impact of unimodal and multimodal interfaces on UX through two procedures:

- In Procedure I (Participants 1–10), the initial phase involved completing the task using the unimodal interface, which exclusively relied on visual interaction. Following the task, participants were asked to fill out the HUROX questionnaire. Subsequently, they repeated the same task, but this time using the multimodal interface, which combined both visual and voice interactions. After completing the task, participants again filled out the HUROX questionnaire (see Table 3)
- In Procedure II (Participants 11–20), the sequence was reversed. Participants first engaged with the task using the multimodal interface and completed the HUROX questionnaire. They then performed the same task using the unimodal interface (visual only), and upon completion of the task, they revisited the HUROX questionnaire (see Table 3).

Table 2
Levels of prior experience with collaborative robots (cobots) [52].

Level	Statement
L0	I have never interacted with a cobot and I did not know about them before now.
L1	I have never interacted with a cobot but I know what they are.
L2	I have interacted at least once with a cobot.
L3	I have already programmed and interacted with a cobot.

3.1.3. Post-task execution phase

Once the interaction phase was complete, an open conversation session was conducted with the participants, in which their emotional states and expectations were explored. The aim of this stage was to create a conducive environment for participants to freely express their emotions and thoughts.

3.2. Task

The task employed in this research was designed to simulate the disassembly process of a refrigerator. It was composed of two interrelated objectives. First, the participants had to disassemble a joint by performing various actions, such as arranging the gaskets, collaborating in the initial placement of the robot, and activating its operation. As can be seen in Fig. 3, the human was the leader of the task and disassembled the electric components. The robot was in charge of extracting the joint, taking into account the location of the human.

The second objective for the participants was to disassemble the electronic components in a 9-step process (Fig. 4), while the robot managed joint removal. Users could refer to the interface for step-by-step guidance, and all components were labelled for easy identification. Prior to the test, participants received training to recognize each component properly.

The robot applied reinforcement learning techniques to detect and avoid collisions with the human, as detailed in the algorithm by Elguea-Aguinaco et al. [58]. This means that the robot performed disassembly away from the person, as depicted in Fig. 5. In Scenario A, if the person is on the right, the robot extracts to the left, and in Scenario B, if the person is on the left, extraction occurs to the right. Participants followed the A-B-A sequence, aiming to extract as many joints as possible while disassembling the boxes, and prioritizing the continuous operation of the robot.

Table 3
Sequence of steps during task execution phase in procedure I and procedure II.

	Procedure I	Procedure II
Step 6	**Perform the task with the unimodal interface:** Participants execute the task by interacting solely with the unimodal interface, emphasizing visual interaction.	**Perform the task with the multimodal interface:** Participants execute the task while interacting with the multimodal interface.
Step 7	**Fill out the HUROX questionnaire:** Participants provide feedback by completing the questionnaire, evaluating their interaction with the robot through the unimodal interface.	**Fill out the HUROX questionnaire:** Participants evaluate their experience by completing the questionnaire after engaging with the robot through the multimodal interface.
Step 8	**Perform the task with the multimodal interface:** Participants repeat the task, this time engaging with the multimodal interface, which combined visual and voice interactions.	**Perform the task with the unimodal interface**: Participants perform the task, interacting solely with the unimodal interface.
Step 9	**Fill out the HUROX questionnaire:** Participants once again fill out the questionnaire, reflecting on their interaction with the robot through the multimodal interface.	**Fill out the HUROX questionnaire:** Participants provide feedback by completing the questionnaire, reflecting on their interaction with the robot through the unimodal interface.

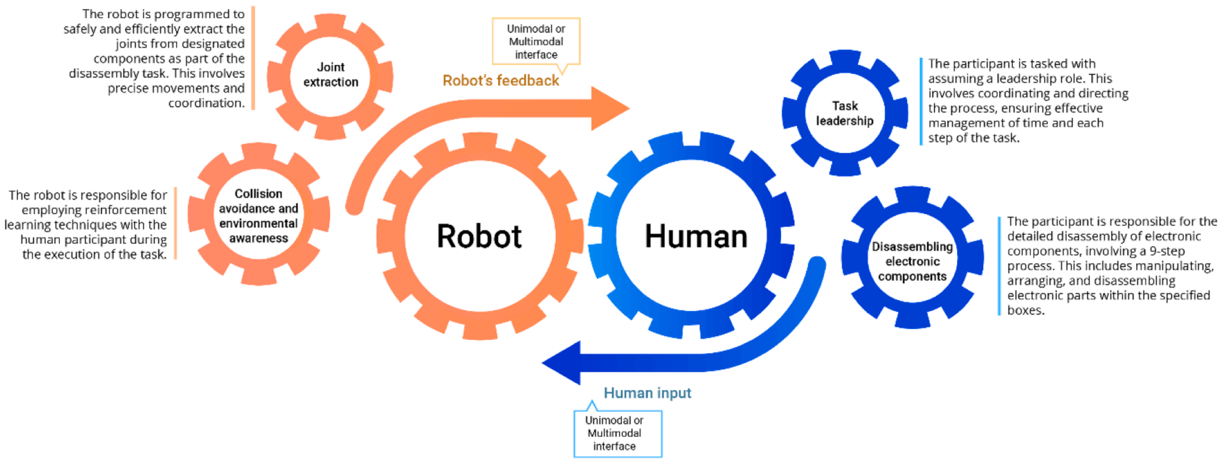


Fig. 3. Distribution of robot and the human responsibilities.

In terms of interface interactions, the study was deliberately limited to two modalities—visual and auditory—to isolate these variables effectively. This methodological decision was part of a phased research approach aimed at establishing a clear baseline of data on fewer variables. Such a focus allowed for a detailed analysis of each mode's impact without the confounding effects of additional variables. This strategic limitation not only simplifies the complexity of the analysis but also enhances the validity of the findings by providing clear, attributable results for each tested interaction modality.

3.3. Environment and robot

The testing procedures took place in a controlled laboratory setting, established to ensure a focused examination of the kinematic factors pertaining to human perception. To further illustrate the technological ecosystem implemented in this study, Fig. 6 presents a schematic diagram of the system architecture and the corresponding data flows and interaction pathways.

For testing, the collaborative robot KUKA LBR iiwa 14 R820 [59] was used, with seven degrees of freedom and torque sensors installed in each joint, along with a workstation featuring an Intel Xeon W-11,855 M CPU at 3.20 GHz, 128 GB of RAM, and an NVIDIA RTX A5000 GPU with 24 GB of VRAM as an external controller [59]. The Robot Operating System (ROS) serves as the standard communication framework for achieving software interoperability in robotics, enabling data exchange among diverse applications through a unified communication channel. Nevertheless, in robot control and machine learning, certain techniques and applications, such as reinforcement learning, require low-latency or real-time control [60]. In reinforcement learning, the agent's interaction with unstructured or dynamic environments often necessitates minimal response latency. The communication architecture inherent to ROS can introduce latency that may hinder its effectiveness in such scenarios, thereby limiting its suitability for time-sensitive tasks [61]. Consequently, for industrial applications where rapid robotic response is critical, direct control mechanisms are often preferred to reduce latency.

To address these limitations, the framework [62] was used to deploy the reinforcement learning control policy in reality. This framework offers a versatile communication interface that supports both native robotic application development on the robot's hardware and software, as well as external control. The latter is facilitated through integration with ROS and direct access via a Python-based Application Programming Interface (API), thereby enabling flexible and low-latency control strategies.

The camera, installed on the ceiling above the workspace, was used to detect the participant's upper-body position and orientation during the disassembly task. As explained in a previous study [58], a computer vision algorithm based on YOLO was employed to identify key anatomical points of the user's upper torso, including shoulders, elbows, wrists, eyes, and nose. This positional data was sent in real time to the reinforcement learning algorithm running on the external PC, which adapted the robot's trajectory to avoid the participant's location. Specifically, the robot extracted the mechanical joint in the direction opposite to the detected human position, ensuring safe human-robot collaboration through adaptive control.

In parallel, the UX monitoring unit collected physiological data from participants using Sennslab software.

3.4. Interfaces

The unimodal interface is exclusively visual, meticulously designed to present essential information in a clear and structured manner. The key design criteria focus on simplicity and clarity, incorporating simple graphics to minimize window complexity and employing familiar language to optimize interaction efficiency. The interface aims to prevent user overload and enhance focus by limiting the number of options presented. Additional considerations such as color, contrast, and visibility are carefully chosen to improve usability and accessibility. An example of this visual UI used in the experimental study is illustrated in Fig. 7.

The multimodal interface extends the capabilities of the previously described unimodal interface by incorporating voice-based communication channels alongside the visual elements, thereby enhancing the user experience. This combination of graphical and auditory elements allows for richer interactions. The voice interface is integrated to complement the visual elements, guiding users through each task with communications about the tasks to be performed and providing feedback on successfully completed tasks. It also conveys the real-time status of the robot, contributing to a more informative and engaging user interaction. The voice commands are designed to extend natural, conversational interactions, aiding users through tasks and offering feedback upon completion.

The design of both interfaces is focused on enhancing usability and ensuring efficient task management within the user interface. The starting page serves as a gateway where participants, once ready, can initiate the process by clicking "Start," ensuring they are adequately prepared before beginning the task. The main menu includes several critical elements such as the Total Task Status, which displays the number of boxes already disassembled, providing a clear and immediate overview of progress. The Robot Status indicates whether the robot is actively working, awaiting the next operation, or needing clearance from the user, thus keeping users informed about the current state of the robot. The Progress Bar for Disassembling Box allows users to visually

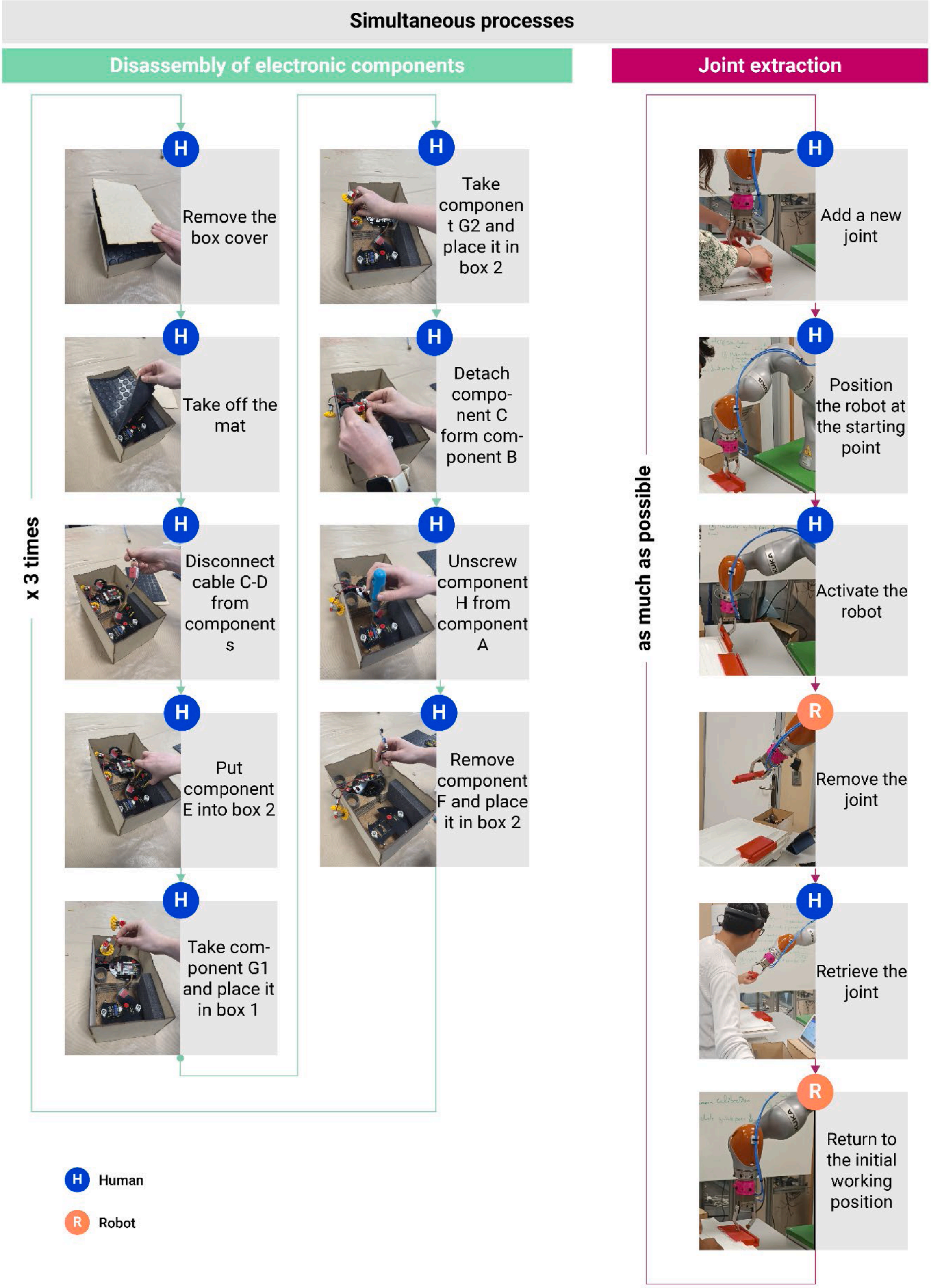


Fig. 4. Flowchart of the steps to complete the task.

track their progress through the disassembly process, enhancing task management. The Subtask Guidance offers detailed descriptions of the specific actions to be executed next and incorporates a "Next" button to facilitate seamless progression through the task sequence, with a "Previous" button allowing users to navigate back to the preceding subtask if needed.

Additionally, the feedback pop-up provides immediate feedback upon the completion of the disassembly of each box, reinforcing successful interactions and encouraging user engagement. This thoughtful integration of visual and auditory elements ensures that the interfaces not only meet functional requirements but also significantly enhance user satisfaction and engagement throughout the interaction process.

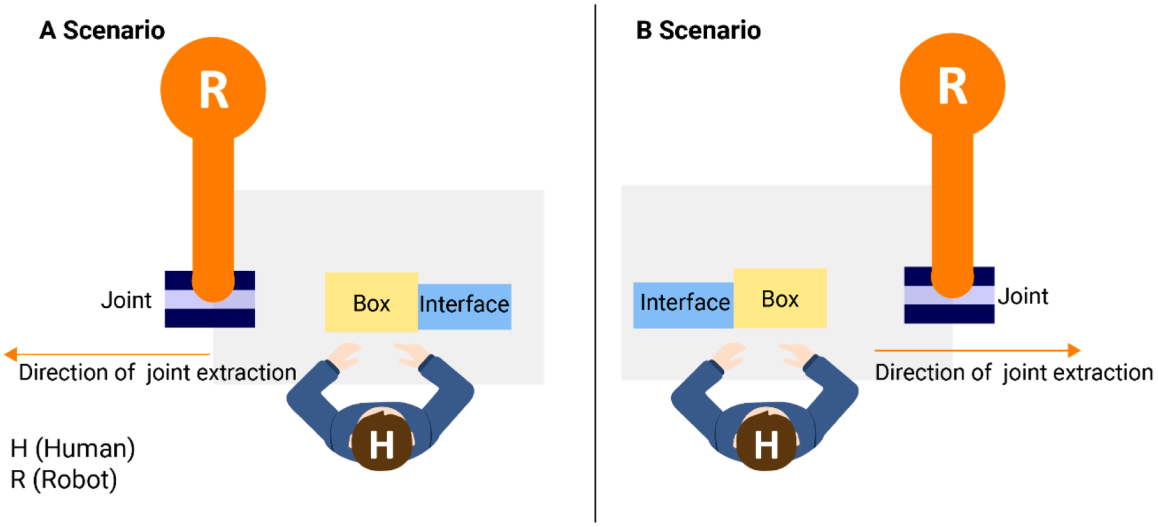


Fig. 5. Set-up of the testing scenarios.

3.5. *Experimental indicators*

Three categories of indicators were used in this evaluation: (i) performance indicators; (ii) physiological values; and (iii) subjective perceptions, which are expressed through quantitative values and reflect the user perspective.

Performance indicators are quantitative and objective measures which assess the effectiveness of the human-robot team in task execution. They serve to objectively evaluate task performance. In this scenario, we focused on a specific indicator: the production index. Unlike tracking overall task completion time or the total number of joints extracted, the production index is calculated as the average time required to extract a single joint. This approach ensures a fair performance comparison that accounts for both speed and precision in the disassembly task.

Physiological indicators are quantitative measures which offer more objective real-time insights than traditional self-report methods to evaluate UX. There are many physiological tools employed in UX studies, and electroencephalography (EEG) has been identified as a robust option [23]. In our study we employed the Diadem EEG [56], which measures the following constructs:

- **Engagement** refers to the participant's level of involvement with, interest in, and connection to the task or activity. It reflects their immersion, attentiveness, and emotional or cognitive investment, indicating the quality of interaction or connection [33–38].
- **Memorization** involves cognitive processes for encoding, retaining, and storing information to form future memories, encompassing activities in acquiring and storing new knowledge or experiences in memory [28–31].
- **Emotional valence** relates to the degree of emotional attraction or aversion in response to stimuli, capturing the subjective sensation of pleasantness or unpleasantness during interaction with the robot in the disassembly task [25–27].
- **Mental workload** signifies the use of cognitive resources in executing a task, including mental effort, attention, and capacity allocation, reflecting the intensity or complexity of the activity [32–35].

User perception values were collected with the HUROX questionnaire [12]. This questionnaire contains 7 constructs in a total of 41 items. These constructs include (i) perceived usefulness (6 items); (ii) perceived ease of use (9 items); (iii) perceived safety (4 items); (iv) controllability (8 items); (v) learnability (3 items); (vi) attitude and intention to use (5 items); and (vii) satisfaction (7 items). Responses were recorded on a 7-point Likert scale.

3.6. *Data processing*

Table 4 summarizes the response and independent variables of the study. Physiological data was recorded with Sennslab, a multimodal data recording software, and analyzed using Sennsmetrics [63].

3.7. *Participants*

In usability studies, it has been claimed that 5 participants are sufficient to identify 80 % of usability problems [64–66]. However, small sample sizes can lead to high variability in test results that cannot be fully adjusted [67]. As concluded in our previous study, there is no widely validated sample size for UX tests with physiological monitoring [23]. According to this review [23], the median sample size in studies utilizing EEG stands at 19.4 participants. Furthermore, half of the EEG case studies feature sample sizes ranging from 9.5 to 24.5 participants.

To ensure robust comparisons, we recruited 20 participants in total, equally distributed between two procedures: Procedure I and Procedure II. Each procedure included 10 participants, with 5 men and 5 women in each group. This sample size was determined considering the practical limitations of EEG monitoring and the necessity for maintaining gender balance, thus ensuring the validity and reliability of the comparisons.

The eligibility criteria for participation were simple: participants needed to volunteer willingly and be prepared to participate under the established conditions (including the use of EEG monitoring). Participants were recruited through a generic email invitation sent to all university employees and students.

The data was collected in controlled laboratory environments to ensure the safety and consistency of the experimental procedures:

- Ten participants aged 22 to 39 years ($M = 30.6$; SD=5.9) participated in procedure I. Previous experience with robots: 2 participants had level L0, 3 participants L1, 4 participants L2, and 1 participant L3.
- Ten participants, equally distributed between men and women made up procedure II. Their age ranged from 25 to 37 years ($M = 27.7$; SD=3.6). Previous experience with robots: 4 participants had level L2, and 6 participants had L3.

Fig. 8 shows a participant interacting with the robot while the facilitator observes the real time EEG indicators on the computer.

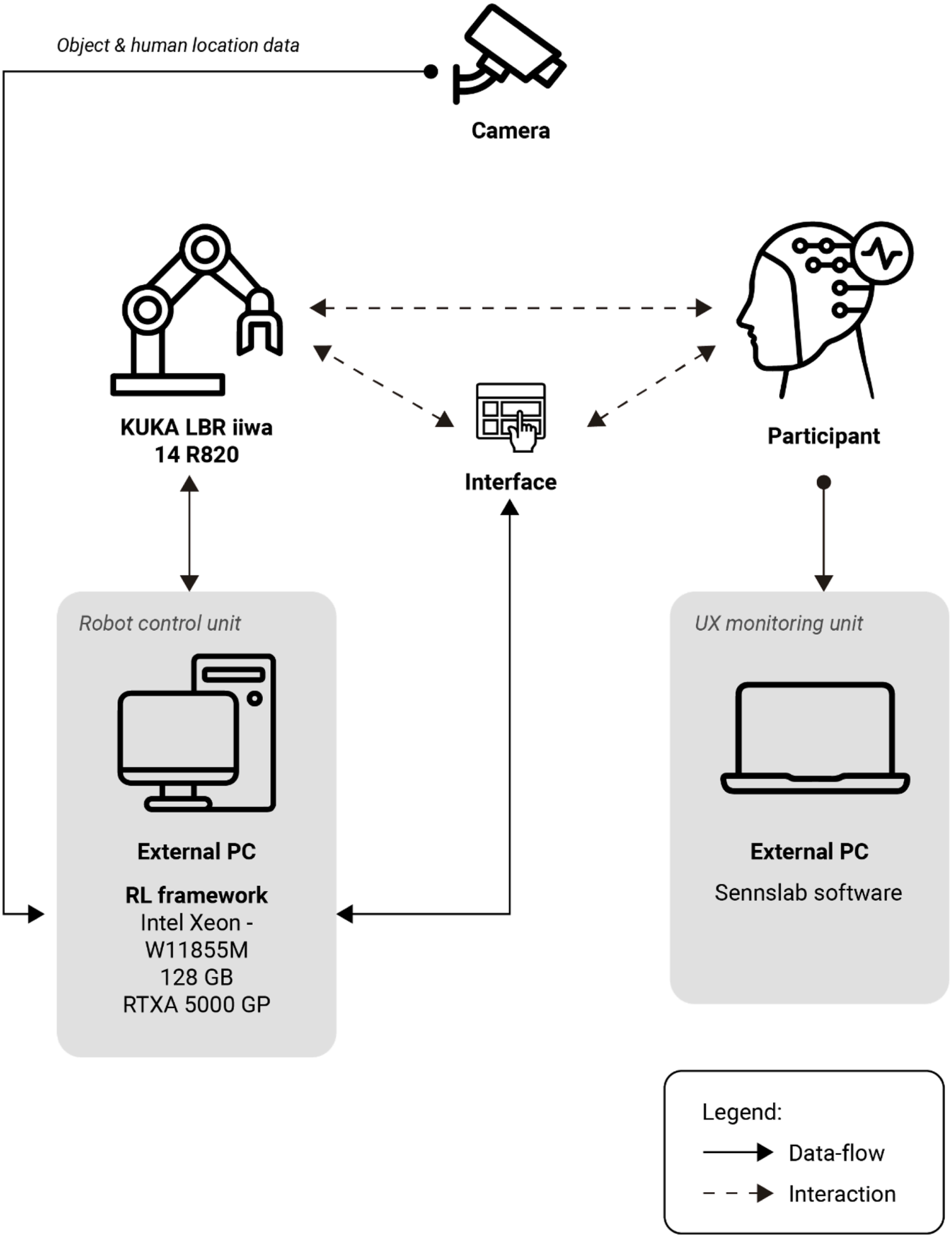


Fig. 6. System architecture and data flow diagram illustrating the interaction and communication between the robot, the participant, camera, interface and the external PCs used for robot control and UX monitoring.

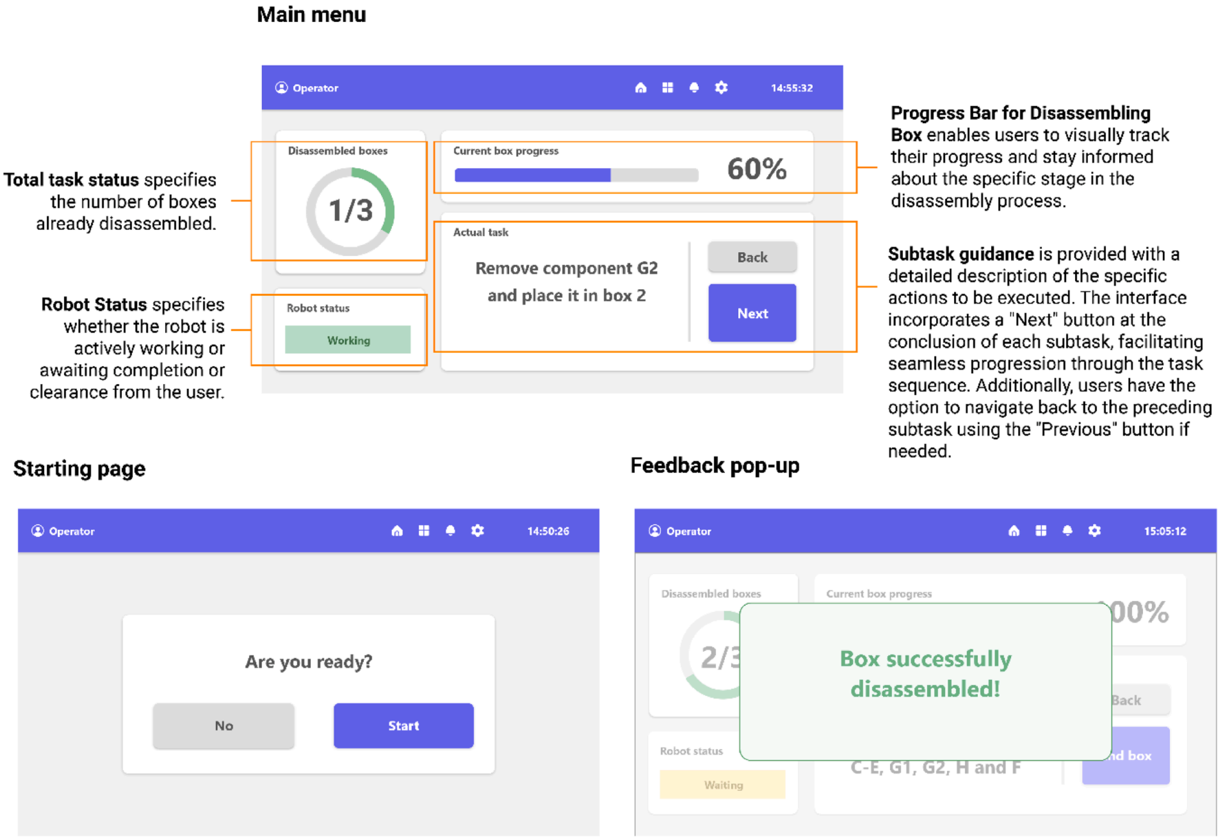
4. Results

Table 5 presents the results obtained for each indicator across each interface, disaggregated by gender. The presented dataset is stored at an online repository [68].

Table 6 presents the results from the *T*-test to determine if the differences between the use of the interfaces were statistically significant.

The physiological indicators obtained by EEG are plotted in Figs. 9 and 10 and analyzed below:

- **Engagement.** Participants demonstrated a higher engagement index when interacting with the unimodal interface (M = 34.86; SD = 4.81) compared to the multimodal interface (M = 34.38; SD = 4.26). However, this difference was not statistically significant (Table 6). Gender-specific analysis revealed that women exhibited higher engagement with the unimodal interface (M = 35.21; SD = 3.76)



Remove component G2 and place it in box 2

Are you ready?

Box successfully disassembled!

Total task status specifies the number of boxes already disassembled.

Robot Status specifies whether the robot is actively working or awaiting completion or clearance from the user.

Progress Bar for Disassembling Box enables users to visually track their progress and stay informed about the specific stage in the disassembly process.

Subtask guidance is provided with a detailed description of the specific actions to be executed. The interface incorporates a "Next" button at the conclusion of each subtask, facilitating seamless progression through the task sequence. Additionally, users have the option to navigate back to the preceding subtask using the "Previous" button if needed.

Starting Page: A starting point where participants, once prepared, can click "Start."

Feedback pop-up: A pop-up that provides feedback once the disassembly of the corresponding box is completed.

Fig. 7. Examples of the visual UI used in the experimental study.

than with the multimodal interface (M = 33.67; SD = 4.89). Conversely, men showed higher engagement with the multimodal interface (M = 35.10; SD = 3.64) compared to the unimodal interface (M = 34.52; SD = 5.87). These differences, however, were not statistically significant (Table 6).

- **Memorization.** The participants exhibited a lower memorization rate when interacting with the multimodal interface (M = 33.73; SD = 6.30) compared to the unimodal interface (M = 37.95; SD = 7.08). Nonetheless, this difference was not statistically significant (Table 6). Gender-specific analysis indicated that both women and men had lower memorization rates with the multimodal interface (Women: M = 35.13; SD = 5.60; Men: M = 32.34; SD = 6.93) than with the unimodal interface (Women: M = 40.56; SD = 6.91; Men: M = 35.34; SD = 6.56). However, these differences were not statistically significant (Table 6).
- **Valence.** The results indicated that participants had a higher valence index during interaction with the multimodal interface (M = 2.75; SD = 3.17) compared to the unimodal interface (M = −0.13; SD = 4.58). This difference was statistically significant (Table 6). Gender-specific analysis showed that both women and men experienced higher emotional valence with the multimodal interface (Women: M = 2.16; SD = 2.12; Men: M = 3.33; SD = 4.00) compared to the unimodal interface (Women: M = −0.66; SD = 2.82; Men: M = 0.40; SD = 5.97). For women, the difference was statistically significant, while for men, it was not (Table 6).
- **Mental workload.** Participants experienced a lower mental workload with the multimodal interface (M = 28.13; SD = 3.17) compared to the unimodal interface (M = 30.99; SD = 2.02). This difference was statistically significant (Table 6). Gender-specific analysis indicated that both women and men exhibited lower mental workload with the multimodal interface (Women: M = 27.74; SD = 3.38; Men: M = 28.52; SD = 3.06) compared to the unimodal interface (Women: M = 31.07; SD = 2.42; Men: M = 30.91; SD = 1.66). These differences were statistically significant (Table 6).

The results obtained from the HUROX questionnaire [12] are presented and analyzed below (Figs. 11 and 12).

- **Perceived Usefulness:** The multimodal interface received a higher mean rating (M = 5.86, SD = 0.91) compared to the unimodal interface (M = 5.56, SD = 0.79). However, this difference was not statistically significant (Table 6). Gender-specific analysis showed that both women and men rated the multimodal interface higher (Women: M = 5.77, SD = 1.09; Men: M = 5.97, SD = 0.72) than the unimodal interface (Women: M = 5.5, SD = 0.97; Men: M = 5.63, SD = 0.74). These differences were not statistically significant (Table 6).
- **Perceived Ease of Use:** No significant differences were found between the two interfaces. Both the multimodal (M = 5.78, SD = 0.75) and unimodal (M = 5.68, SD = 0.79) interfaces received similar ratings. Consequently, no statistically significant differences were observed (Table 6). Gender-specific analysis revealed that women rated the unimodal interface slightly higher (M = 5.82, SD = 0.90) than the multimodal interface (M = 5.79, SD = 0.78), while men rated the perceived ease of use higher for the multimodal interface (M = 5.77, SD = 0.76) than for the unimodal interface (M = 5.54, SD = 0.68). These differences were not statistically significant (Table 6).
- **Perceived Safety:** The multimodal interface recorded a slightly higher mean rating (M = 5.33, SD = 1.19) than the unimodal interface (M = 5.14, SD = 1.12). However, this difference was not statistically significant (Table 6). Gender-specific analysis showed that women rated the unimodal interface slightly better (M = 5.53, SD = 1.10) than the multimodal interface (M = 5.28, SD = 1.11).

Table 4
Summary of the variables involved in the study.

Type of variable	Variable category	Variable name	Description
Independent variables		Type of interface	Unimodal interface (visual). Multimodal interface (visual and auditive).
Response variables	Performance indicator	Production index	Average time needed to disassemble a single joint.
	Physiological indicators	Emotional valence	Level of attraction [25–27]. Scoring ranges from −100 % to 100 %.
		Memorization	Intensity of cognitive processes related to forming future memories [28–31]. Scoring ranges from 0 % to 100 %.
		Workload	The mental effort or cognitive resources used to complete a task [32–35]. Scoring ranges from 0 % to 100 %.
		Engagement	The degree of involvement or connection [33–38]. Scoring ranges from 0 % to 100 %.
	Perceptual indicators	Perceived usefulness	The participant's subjective assessment of the practicality and benefit. Participants evaluated each interface using a 7-point Likert scale.
		Perceived ease of use	The participant's perception of how easy it is to use. Participants evaluated each interface using a 7-point Likert scale.
		Perceived safety	The participant's subjective assessment of the safety. Participants evaluated each interface using a 7-point Likert scale.
		Controllability	The degree to which the participant feels in control. Participants evaluated each interface using a 7-point Likert scale.
		Learnability	The ease with which a participant can learn and understand how to use. Participants evaluated each interface using a 7-point Likert scale.
		Attitude and intention to use	The participant's overall attitude towards and intention to continue using. Participants evaluated each interface using a 7-point Likert scale.
		Satisfaction	The participant's overall satisfaction. Participants evaluated each interface using a 7-point Likert scale.

Conversely, men rated the multimodal interface higher (M = 5.38, SD = 1.32) compared to the unimodal interface (M = 4.75, SD = 1.05). These differences were not statistically significant (Table 6).

- **Controllability:** The unimodal interface scored a higher mean rating (M = 4.65, SD = 1.29) than the multimodal interface (M = 4.39, SD = 1.09). However, this difference was not statistically significant (Table 6). Gender-specific analysis indicated that both women and men rated the unimodal interface higher in terms of controllability (Women: M = 4.66, SD = 1.15; Men: M = 4.64, SD = 1.5) compared to the multimodal interface (Women: M = 4.51, SD = 0.83; Men: M = 4.26, SD = 1.34). These differences were not statistically significant (Table 6).
- **Learnability:** Both the unimodal interface (M = 6.26, SD = 0.72) and multimodal interface (M = 6.28, SD = 0.80) received similar ratings in this aspect. Consequently, the difference was not statistically significant (Table 6). Gender-specific analysis showed that women rated learnability higher for the unimodal interface (M = 6.47, SD = 0.57) compared to the multimodal interface (M = 6.17, SD = 0.98), whereas men rated learnability higher for the multimodal interface (M = 6.4, SD = 0.6) than the unimodal interface (M = 6.07, SD = 0.83). These differences were not statistically significant (Table 6).
- **Attitude and Intention to Use:** Both the unimodal interface (M = 5.91, SD = 1.00) and the multimodal interface (M = 5.96, SD = 0.86) reported similar scores, and the difference was not statistically significant (Table 6). Gender-specific analysis indicated that women rated their attitude and intention to use the unimodal interface higher (M = 6.24, SD = 0.78) than the multimodal interface (M = 6.1, SD = 0.90). Conversely, men rated their attitude and intention to use the multimodal interface higher (M = 5.82, SD = 0.84) compared to the unimodal interface (M = 5.58, SD = 1.12). These differences were not statistically significant (Table 6).
- **Satisfaction:** The multimodal interface received a slightly higher mean rating (M = 5.54, SD = 0.94) compared to the unimodal interface (M = 5.44, SD = 0.85). Once again, this difference was not statistically significant (Table 6). Gender-specific analysis showed that women reported similar average satisfaction with both the multimodal interface (M = 5.64, SD = 0.93) and the unimodal interface (M = 5.61, SD = 0.66). Men, on the other hand, showed slightly higher satisfaction with the multimodal interface (M = 5.43, SD = 0.98) compared to the unimodal interface (M = 5.26, SD = 1.00). These differences were not statistically significant (Table 6).

5. Discussion

5.1. Validation of the hypothesis

Our findings indicate that the use of a multimodal interface leads to lower levels of memorization and mental workload than when using the unimodal interface. However, this difference was statistically significant only in the mental workload indicator. It is important to note that this validation was observed in both women and men, which enhances the robustness of the results.

In line with the formulated hypothesis, emotional valence increased in interactions with the multimodal interface, and this difference was also found to be statistically significant. Engagement, however, scored slightly lower for the multimodal interface, although the difference did not prove to be statistically significant.

Furthermore, it should be noted that this improvement extended beyond cognitive and mental workload aspects, to a more positive overall perception of the UX, as evidenced by the HUROX questionnaire results. All components of the HUROX questionnaire, with the exception of the Controllability construct, reported higher scores when interacting with the multimodal interface.

5.2. Impact of the interfaces on human factors

We identified the impact of the interfaces on human factors, including:

Fig. 8. Human-robot interaction in the experimental study.

Table 5
Results obtained for each indicator across interfaces and disaggregated by gender.

		Unimodal Interface			Multimodal interface		
		All	Women	Men	All	Women	Men
Performance indicator	Production ratio	0:48	0:51	0:45	0:49	0:51	0:47
Physiological indicators	Engagement	34.86 (SD=4.81)	35.21 (SD=3.76)	34.52; (SD=5.87)	34.38 (SD=4.26)	33.67 (SD=4.89)	35.10 (SD=3.64)
	Memorization	37.95 (SD=7.08)	40.56 (SD=6.91)	35.34 (SD=6.56)	33.73 (SD=6.30)	35.13 (SD=5.60)	32.34 (SD=6.93)
	Emotional valence	−0.13 (SD=4.58)	−0.66 (SD=2.82)	0.40 (SD=5.97)	2.75 (SD=3.17)	2.16 (SD=2.12)	3.33 (SD=4.00)
	Mental workload	30.99 (SD=2.02)	31.07 (SD=2.42)	30.91 (SD=1.66)	28.13 (SD=3.17)	27.74 (SD=3.38)	28.52 (SD=3.06)
Perceptual indicators	Perceived Usefulness	5.56 (SD=0.79)	5.5 (SD=0.97)	5.63 (SD=0.74)	5.86 (SD=0.91)	5.77 (SD=1.09)	5.97 (SD=0.72)
	Perceived Ease of Use	5.68 (SD=0.79)	5.82 (SD=0.90)	5.54 (SD=0.68)	5.78 (SD=0.75)	5.79 (SD=0.78)	5.77 (SD=0.76)
	Perceived Safety	5.14 (SD=1.12)	5.53 (SD=1.10)	4.75 (SD=1.05)	5.33 (SD=1.19)	5.28 (SD=1.11)	5.38 (SD=1.32)
	Controllability	4.65 (SD=1.29)	4.66 (SD=1.15)	4.64 (SD=1.5)	4.39 (SD=1.09)	4.51 (SD=0.83)	4.26 (SD=1.34)
	Learnability	6.26 (SD=0.72)	6.47 (SD=0.57)	6.07 (SD=0.83)	6.28 (SD=0.80)	6.17 (SD=0.98)	6.4 (SD=0.6)
	Attitude and intention to use	5.91 (SD=1.00)	6.24 (SD=0.78)	5.58 (SD=1.12)	5.96 (SD=0.86)	6.1 (SD=0.90)	5.82 (SD=0.84)
	Satisfaction	5.44 (SD=0.85)	5.61 (SD=0.66)	5.26 (SD=1.00)	5.54 (SD=0.94)	5.64 (SD=0.93)	5.43 (SD=0.98)

Table 6
T-Test Results to determine significant differences between interfaces (considering α=0.05). Statistically significant values are highlighted in bold.

		All	Women	Men
Performance indicator	Production ratio	0.7392	0.2088	0.3255
Physiological indicators	Engagement	0.7404	0.4416	0.7948
	Memorization	0.0538	0.0700	0.3326
	Emotional valence	**0.0270**	**0.0217**	0.2154
	Mental workload	**0.0018**	**0.0221**	**0.0480**
Perceptual indicators	Perceived Usefulness	0.2853	0.5713	0.3207
	Perceived Ease of Use	0.7009	0.9305	0.5018
	Perceived Safety	0.6107	0.6201	0.2567
	Controllability	0.4921	0.7434	0.5596
	Learnability	0.9454	0.4181	0.3189
	Attitude and intention to use	0.8660	0.7141	0.5944
	Satisfaction	0.7263	0.9380	0.7053

- **Reduction in Memorization and Mental Workload using the multimodal interface:** The analysis of the physiological indicators indicates that memorization and mental workload levels decrease when using the multimodal interface. Such a reduction could lead to enhanced cognitive efficiency during interactions, as the ability to exchange information and receive feedback through multiple modalities may facilitate assimilation of procedures and task details. This is particularly significant in an industrial setting where accuracy and speed are crucial. It can also be interpreted as a less demanding interaction experience. By providing multiple channels of information, the multimodal interface might have reduced the overall cognitive burden by distributing information more effectively. As a result, participants may have experienced a sense of fluidity and comfort during task execution.
- **Usefulness and experience perspectives:** The high perceived usefulness score for the multimodal interface suggests that participants found additional benefits when interacting with an interface that combined both visuals and voice. This may be due to the multimodal interface providing greater interactive flexibility and variety than the unimodal, which can enhance the effectiveness and efficiency of the interaction. The task execution sequence, in which participants performed the task first with the multimodal interface and then with the unimodal interface, may also have influenced the results. It is possible that the familiarity gained during the first execution with the multimodal interface improved efficiency and adaptation during the second execution with the unimodal interface. This could explain why no significant differences in the evaluated dimensions were observed between the interfaces. The high degree of learnability of the system may also have contributed to task agility, regardless of the interface used in the second instance.

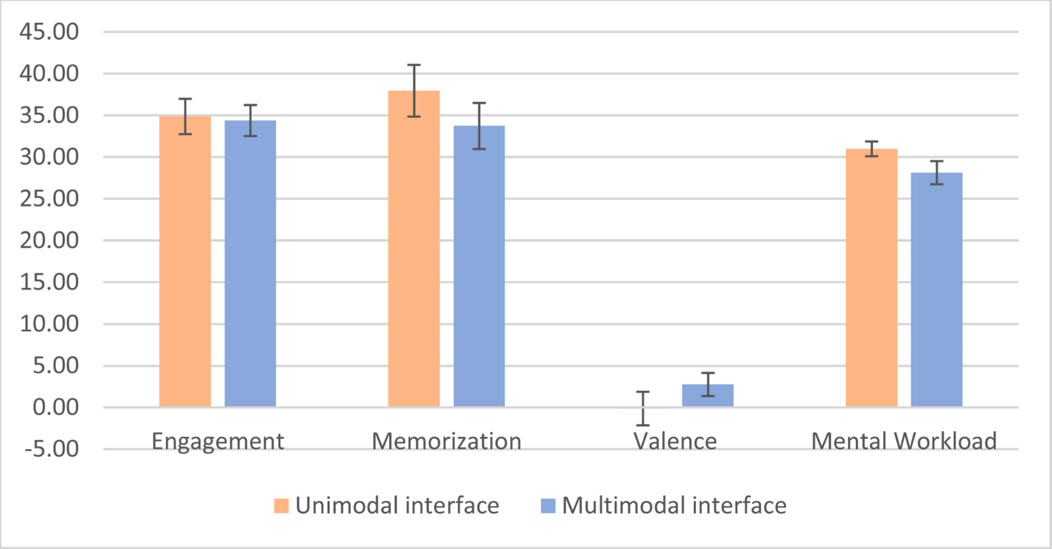


Fig. 9. Results of Physiological Indicators: comparison between Unimodal and Multimodal interfaces, merging the results of both procedures.

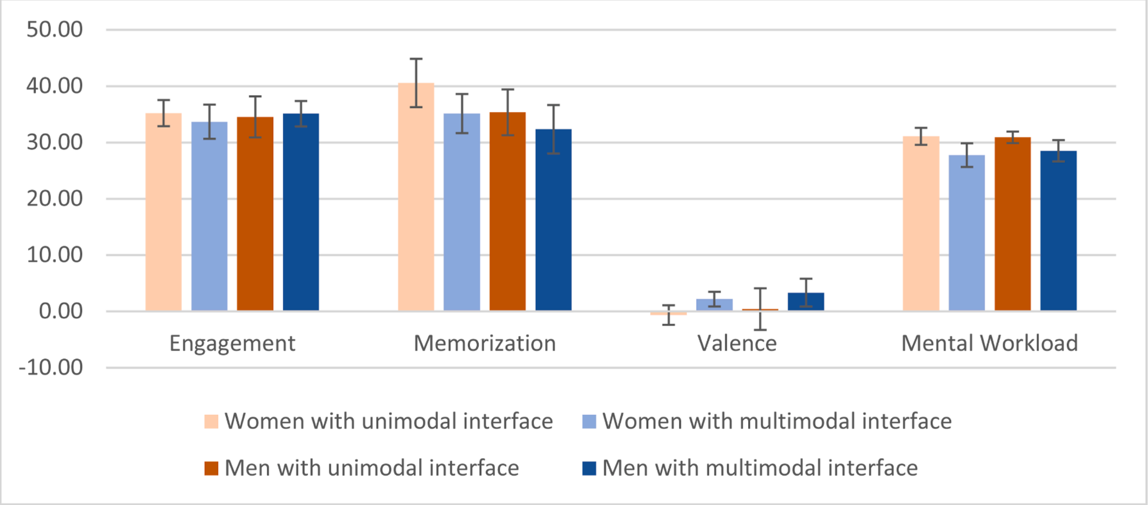


Fig. 10. Results of Physiological Indicators: comparison between Unimodal and Multimodal interfaces, merging the results of both procedures and disaggregated by gender.

- **Reduced Perceived Control in Multimodal Interface:** The incorporation of multiple input modalities and feedback channels in a multimodal interface appears to have led to a perceived reduction in control. Managing diverse input types and feedback mechanisms could have introduced complexity and uncertainty, in contrast with the more straightforward unimodal interface. Navigating through multiple modalities may also have contributed to a perceived decrease in controllability, especially for users accustomed to simpler, more direct interactions. Familiarity with each interface type and design significantly shapes perceptions of ease of use and controllability. Ensuring a unified and intuitive design for multimodal interfaces is critical for maintaining a sense of control while benefiting from diverse input and feedback.

5.3. Group differences analysis

We conducted an analysis to identify significant differences in the studied indicators based on various group conditions. These conditions include the procedure used (Procedure I or Procedure II), the gender of the participants (female or male), their age (under 30 or over 30), and their experience with robots (no experience, denoted as L0 or L1, or experienced, denoted as L2 or L3, in the sociodemographic questionnaire). The analyses were conducted using *T*-Tests, with a significance level of $\alpha = 0.05$. The results are set out in Table 7 and are summarized as follows:

Our findings revealed no significant differences in the production index under any conditions for either interface, indicating a consistent performance across different groups. However, we observed notable variances in physiological responses; participants in Procedure I demonstrated higher engagement values in the unimodal interface compared to those in Procedure II, suggesting a procedure-dependent response in engagement levels.

In terms of perceived utility, participants in Procedure I rated the multimodal interface significantly higher than those in Procedure II, reflecting a perceived enhanced usefulness of the multimodal system. This perception was also mirrored in the safety ratings; the unimodal interface was considered safer by participants in Procedure I compared to those in Procedure II, and a similar trend was noted for the multimodal interface. It appears that participant comparisons between procedures and their prior experience influenced these perceptions,

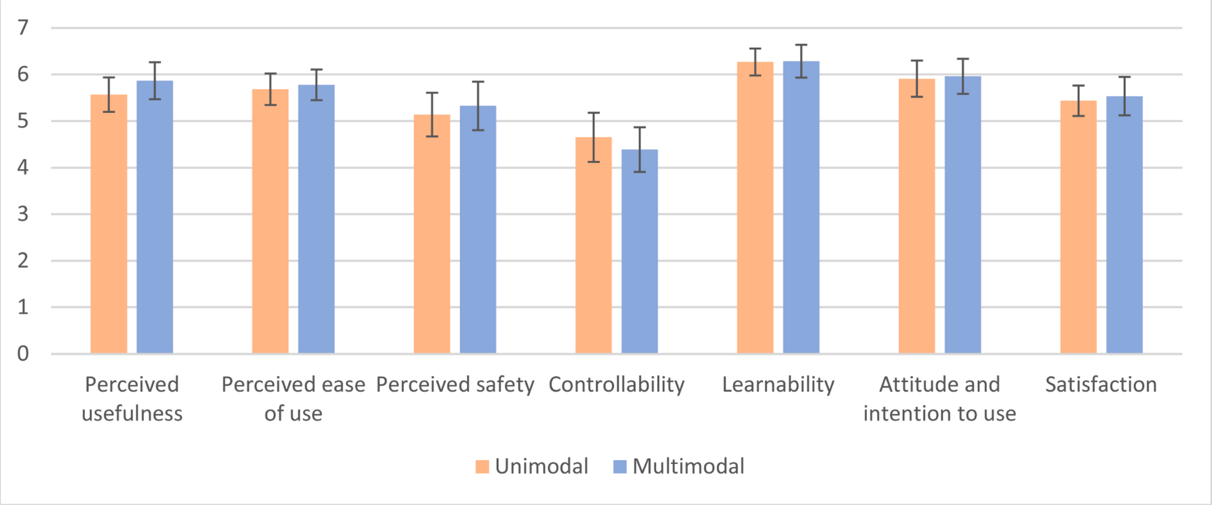


Fig. 11. Results of Perceptual Indicators (using HUROX questionnaire): comparison between Unimodal and Multimodal Interfaces of both procedures.

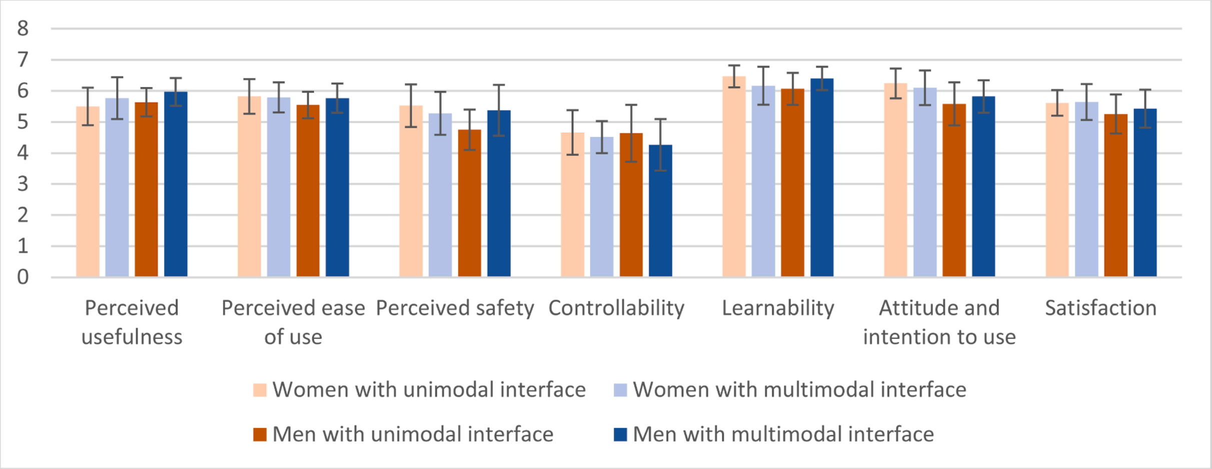


Fig. 12. Results of Perceptual Indicators (using HUROX questionnaire): comparison between Unimodal and Multimodal Interfaces in Procedure II, disaggregated by gender.

Table 7

T-Test results for studied indicators: Significant differences by procedure, gender, age, and experience at α = 0.05. Significant differences are highlighted in bold.

		Unimodal				Multimodal			
		Procedure (Procedure I/ Procedure II)	Gender (Women/ Men)	Age (<30/ >30)	Experience (L0 and L1/L2 and L3)	Procedure (Procedure I/ Procedure II)	Gender (Women/ Men)	Age (<30/ >30)	Experience (L0 and L1/L2 and L3)
Performance indicator	**Production Rate**	0.2443	0.2088	0.0935	0.4271	0.0817	0.3255	0.8550	0.1266
Physiological indicators	**Engagement**	**0.0376**	0.7591	0.6632	0.0807	0.3462	0.4694	0.2233	0.7419
	Memorization	0.9267	0.1007	0.4933	0.4068	0.2432	0.3362	0.1211	0.7754
	Valence	0.0903	0.6208	0.7965	0.1891	0.3011	0.4289	0.1140	0.5282
	Mental workload	0.5275	0.8627	0.2823	0.2316	0.7014	0.5962	0.2899	0.9182
Perceptual indicators	**Perceived usefulness**	0.6710	0.7343	0.1678	0.0903	**0.0089**	0.6353	0.3816	0.1937
	Perceived ease of use	0.6507	0.4488	0.0651	0.3849	0.1313	0.9493	0.2203	0.9463
	Perceived safety	**0.0035**	0.1244	0.5310	0.2018	**0.000002**	0.8568	0.0577	**0.0095**
	Controllability	0.1119	0.9669	**0.0226**	**0.0331**	0.3999	0.6238	**0.0019**	0.0877
	Learnability	0.8436	0.2268	0.4287	0.5645	**0.0490**	0.5327	0.5311	0.8827
	Attitude and intention to use	0.6349	0.1445	0.1235	0.4084	0.3111	0.4815	0.1832	0.5319
	Satisfaction	0.1532	0.3642	0.4513	0.6739	**0.0007**	0.6233	0.7692	0.3412

especially as participants with no experience (L0) perceived higher safety.

Controllability differences were significant across age groups in both interfaces, with younger participants (under 30) feeling more in control. Experience also played a role, particularly with the unimodal interface where experienced participants rated higher controllability. Interestingly, learnability showed significant differences only in the multimodal interface between procedures, with Procedure I scoring higher.

Finally, satisfaction levels with the multimodal interface were consistently rated higher by participants in Procedure I compared to those in Procedure II, reinforcing the observed trend that the multimodal interface was generally favored under the conditions of Procedure I.

5.4. *The gender perspective*

An essential consideration in evaluating HRI in industrial environments is potential gender differences in perception and performance. Analyzing the data from this perspective is crucial to addressing the existing gender digital gap.

When the performance indicators were analyzed in terms of gender, the results revealed a notable absence of significant differences. Both men and women displayed similar responses in terms of performance improvement during the second task execution, regardless of the type of interface used. This observation indicates that gender does not appear to be a determining factor in the adaptation and learning of the collaborative task in this specific industrial context.

Furthermore, the evaluation of physiological indicators reinforced this finding. Analysis showed that the differences between unimodal and multimodal interfaces do not appear to be influenced by gender. Both genders consistently reported a reduction in levels of memorization and cognitive load with the multimodal interface, regardless of the sequence of use.

The results of the HUROX questionnaire disaggregated by gender painted a similar picture. No significant differences were found between men and women in any of the evaluated interfaces in the two procedures. Both genders responded similarly to questions regarding perceived utility, perceived ease of use, perceived safety, controllability, learnability, attitude and intention to use, and satisfaction. This indicates that the perception of the interfaces was not influenced by the gender of the participants.

These findings indicate that in this specific industrial setting, there is a consistent level of adaptation to and acceptance of both unimodal and multimodal interfaces across genders. This uniformity suggests that the interfaces are effectively designed to accommodate a diverse user base without bias towards one gender. However, given the small sample size and ongoing gender inequalities in technology fields, it remains imperative to continue investigating new technologies with a focus on gender. Always disaggregating results by gender will help ensure that our advancements are truly inclusive and address the nuances that might otherwise perpetuate existing disparities.

5.5. *Reliability of the HUROX questionnaire*

The reliability of the HUROX questionnaire was evaluated separately for each interface. Table 8 sets out the Cronbach's alpha coefficients for each construct under both interface conditions. All dimensions reported a score higher than 0.60, indicating the internal consistency and reliability of the HUROX questionnaire dimensions for both the unimodal and multimodal interfaces [69].

Table 8
Cronbach's Alpha Coefficients for the HUROX Questionnaire.

Construct	Unimodal	Multimodal
Perceived Usefulness	0.8312	0.9034
Perceived Ease of Use	0.8241	0.7559
Perceived Safety	0.6181	0.6363
Controllability	0.8677	0.7936
Learnability	0.7349	0.8521
Attitude and Intention to Use	0.8013	0.7001
Satisfaction	0.7576	0.7870

5.6. *Limitations*

This study acknowledges certain limitations that must be considered. First, although the sample size of 20 participants aligns with the average in EEG studies [23], which is approximately 19.5, the limitations of this sample size extend beyond mere numbers. While our participant count is adequate for preliminary investigations and aligns with industry norms for EEG research, further studies with larger and more diverse samples are recommended to enhance the reliability and generalizability of our findings. Expanding the sample size would not only improve the statistical power of future studies but also allow for a more nuanced understanding of how different user groups interact with unimodal and multimodal interfaces.

The scope of interaction modalities examined in this study was intentionally limited to control for study variables effectively. This approach was strategic to isolate the effects of each modality on user experience. However, this limitation may restrict the broader applicability of the results to other forms of interaction. Future research should therefore consider exploring additional modalities, such as haptic feedback and combinations thereof, to achieve a comprehensive view of how various modalities influence user interactions within multimodal user interfaces.

Additionally, while our experimental setup proved effective in a controlled laboratory setting, the use of EEG presents certain challenges for real-world application. EEG devices can be somewhat intrusive, which may limit their practicality outside of laboratory environments. Enhancing the non-intrusiveness of physiological monitoring devices is crucial for their adoption in real-world industrial settings [70].

Another limitation arises from the allocation of participants into Procedure I and Procedure II, which aimed to ensure a balanced gender distribution but did not account for variations in participants' prior experience with robots. Although the levels of experience were documented, the random allocation led to discrepancies in prior experience between the two groups. This aspect, while a result of chance, introduces an additional variable that could influence the outcomes. Future studies might consider stratifying participants by experience levels to control this variable more rigorously.

Despite these limitations, it is important to note that the study has effectively addressed the formulated hypothesis and research questions. The findings contribute valuable insights into the field, even as they highlight areas for further inquiry and improvement. These limitations, far from undermining the study, instead underscore the complexity of researching human-robot interactions and pave the way for subsequent research efforts that can build on this foundational work.

6. Conclusions

Does using multimodal interfaces in HRI reduce the need for workers to remember information and mental effort? Does it make users more engaged and positive towards the experience? Does it improve their overall perception of the UX compared to using a unimodal interface? To determine the impact of interface type on human factors in collaborative work environments, we undertook a comprehensive UX analysis of the impact of interface type on human factors. The protocol employed a set of metrics organized into three domains: (i) performance; (ii) physiological indicators; and (iii) perceptual indicators, aiming to investigate the UX through a holistic and human-centered approach.

Our findings show no significant differences in performance between the two interfaces. However, the results reveal notable physiological differences. Using the multimodal interface led to reduced mental effort and increased emotional valence. While the difference in memorization was not statistically significant, the multimodal interface tended to be associated with lower levels of this metric. In terms of engagement, the unimodal interface scored higher, although it was not statistically significant. As for perceptual indicators, no statistically significant differences were observed. However, participants tended to find the multimodal interface more useful, easier to use, safer, and more satisfying. Conversely, the unimodal interface gave users a greater sense of control. Both interfaces ranked similarly in terms of ability and attitude and intention to use.

The study also found that gender played no significant role in how participants adjusted to and accepted the interfaces, regardless of type. Men and women alike displayed comparable levels of acceptance and adoption in all aspects assessed.

In light of these findings, the multimodal interface emerges as a favorable choice, offering enhanced accessibility for all individuals. Its benefits extend to lower mental workload and higher emotional valence, but the key advantage lies in its inclusive design. By catering to diverse physiological and perceptual needs, the multimodal interface ensures that the system is more accessible and user-friendly for a broader range of individuals. This inclusive approach complements the goal of developing technology that meets diverse user preferences and abilities. It promotes the development of an industry that values equity and aligns with the objectives of Industry 5.0, which aims to establish a more inclusive and user-centric technological landscape [6].

In future HRI interfaces, the challenge of enhancing user comprehension and perception can be addressed by combining various interface modalities, such as visual, auditory, and haptic feedback. Effectively integrating these multiple feedback modes can promote clear and efficient communication and significantly improve the overall quality of the HRI experience. However, these modalities must be combined with care. One important factor to consider is their complementary nature, as each modality has unique strengths and weaknesses, and the optimal combination requires more investigation. Further research comparing interface types and their impact on user perception could offer insights into designing more effective HRI systems that meet user preferences.

Ethical approval and informed consent

This study was approved by the Research Ethics Committee of Mondragon Unibertsitatea under approval number IEB-20241002B Informed consent was obtained from all participants prior to their participation. Consent was provided in written form, with participants signing a form outlining the study's purpose, procedures, and their rights, including the right to withdraw from the study at any time.

CRediT authorship contribution statement

Ainhoa Apraiz: Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ganix Lasa:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Maitane Mazmela:** Writing – review & editing, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Nestor Arana-Arexolaleiba:** Writing – review & editing, Supervision, Resources. **Íñigo Elguea:** Writing – review & editing, Supervision, Resources. **Oscar Escallada:** Writing – review & editing, Supervision. **Nagore Osa:** Writing – review & editing, Supervision. **Amaia Etxabe:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The datasets presented in this study can be found in online repositories. The name of the repository and accession number can be found below: https://hdl.handle.net/20.500.11984/6952.

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