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Managing Human Factors: An Innovative Frameworks for Human-Robot Collaboration: Insights into Interaction Modalities Causing Workload

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This study examines interaction modalities' impact on workload in human-robot collaboration within Industry 5.0. Using a framework inspired by Wickens' Multiple Resource Theory, it highlights the negative impact of linguistic tasks and the positive effects of tactile feedback on workload. Input-assist interactions, particularly in visual-spatial contexts, show potential for optimization, while autonomy and environmental factors like robot size and speed further influence workload. The findings suggest practical strategies for enhancing collaboration and call for exploring underutilized modalities and complementary metrics to improve workload assessments in future research.

Keywords: Human-Robot Collaboration, Occupational health, Sensory modalities, Cognitive Workload, Workload, Multimodal, Interaction.

1. Introduction

The Fifth Industrial Revolution is characterized by the sophisticated integration of innovative technologies such as collaborative robots into assembly line tasks AR, VR, AI and teleoperation, etc (Akpan & Offodile, 2024; Nahavandi, 2019; Budhwar et al., 2023). Unlike Industry 4.0, which primarily emphasizes the automation and digitization of manufacturing processes for increased efficiency. A principal concern in Industry 5.0 is the rigorous adherence to Occupational Health and Safety (OHS) principles, critically emphasizing the human factors in manufacturing settings. Human factors are defined as the interdisciplinary field that focuses on optimizing the relationship including safety, operator well-being, productivity, etc., between operators and the outer environment in both physical and cognitive aspects, in this article, particularly discussed in the context of human-robot collaboration (HRC) within Industry 5.0. The deployment of collaborative robots, or 'cobots' combination with other technology such as AR, VR, AI, etc., in manufacturing settings introduces innovative modes of human-robot interaction. Although these robots are engineered to reduce physical demands on human workers, thereby potentially mitigating physical strain, they concurrently introduce new operational risks (Weiss et al., 2021), (Giallanza et al., 2024). These risks stem from the need for operators to adapt to more sophisticated and flexible interaction modalities that require a blend of cognitive soft skills not previously demanded in traditional manufacturing settings (Villani et al., 2022), (Iani et al., 2021). So managing the human factors approaching by manage the cognitive and physical load can be a possible orientation. The way of interactions influences cognitive ergonomics in the current complexity such as the new manufacturing setting, new way of handing the machine in factory such as robot, and the stress of dealing with errors in the new way of manufacturing, (Caruana & Francalanza, 2022; (Akpan & Offodile, 2024). In the neuroscience field, Bijleveld (Bijleveld, 2023) highlights that system failures significantly elevate cognitive load, often surpassing the cognitive demands of traditional manufacturing systems. Addressing these challenges necessitates linking cognitive load to innovative manufacturing processes by leveraging theories capable of analyzing energy consumption and optimizing both cognitive and physical demands. Such optimization not only enhances operator effectiveness and safety but also ensures the smooth operation of complex processes. Wickens' Multiple Resource Theory (MRT) provides a foundational framework for predicting cognitive workload during dual-task scenarios, such as driving while navigating a map (Wickens, 2002, 2008). According to this theory, cognitive load varies depending on the sensory modalities engaged, such as auditory, linguistic, spatial, tactile, and visual inputs (Wickens, 2024a). The theory conceptualizes human information processing into three stages: perception, cognition, and response. However, while MRT offers valuable insights, its general guidance is insufficient to address the complexities of modern manufacturing, where emerging technologies like AR and VR involve more intricate and unexpected modalities.

Inspired by MRT, this paper proposes a new framework (Figure 1) that integrates physical and cognitive workload considerations to optimize human-centered design. The positing of modalities is from MRT, the output and input are added-on. In this framework, humans are modeled as information-processing systems, where interaction modalities are categorized into inputs and outputs. Inputs represent stimuli from the external environment, such as typing on a keyboard, while outputs denote responses, such as visualizing data on a screen. This analogy enables a systematic perspective on workload management, offering practical guidance for managers, designers, and companies to enhance worker well-being and productivity.

A well-established and widely accepted metric for assessing workload, the NASA Task Load Index (NASA-TLX), provides an effective standard for evaluating cognitive and physical demands (Hart, n.d.). Compared to emerging tools such as Heart Rate Variability (HRV) and Galvanic Skin Response (GSR), NASA-TLX remains a reliable benchmark. Incorporating NASA-TLX into the proposed framework enables a deeper understanding of how various sensory modalities influence workload, reinforcing its role as a foundational tool for evaluating operator performance in modern industrial settings.

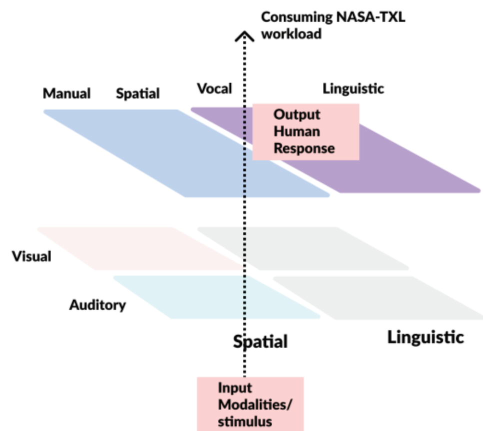

Fig. 1. A margin framework based on the MRT(Wickens, 2024b)

This review aims to consolidate experiments related to sensory modalities and contextualize their findings within the proposed framework. By leveraging NASA-TLX scores, the framework identifies opportunities for advancing robotics research, refines MRT through clustering modalities, and highlights unexplored sensory interactions. By incorporating multi-sensory inputs—including visual, auditory, textual, and 3D views—the framework fosters the potential for improving cognitive and physical workload management, aligning with the goals of Industry 5.0.

2. Methodology

A structured methodological approach (Fig.2) was employed to systematically analyse relevant research on synesis measurements. This study utilized the Scopus database, meticulously following defined steps to retrieve articles, which were subsequently reviewed for inclusion in the final full-text analysis. Parallelly, a search using the same inclusion-exclusion criteria was conducted on the Scopus. The initial selection of keywords was derived from the literature on robot collaboration. The search was further refined to include terms directly associated with the assessment methods: "physiological," "psychological," "behavioral," "EEG," "ECG," "eye tracking," and "NASA- TLX." To ensure relevance, the scope was narrowed to tasks involving "assembly."

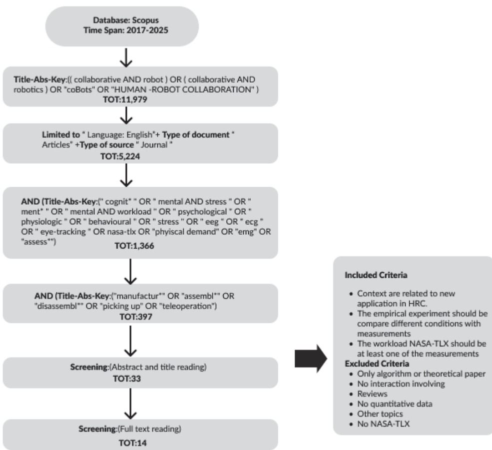

Fig. 2. Protocol for searching and screening

On December 20, 2024, the completion of the search phase marked the transition to a detailed manual assessment of the retrieved articles. The selection of articles adhered to the following inclusion criteria: (1) studies must involve empirical experiments, (2) there must be a comparison between different interaction modalities, (3) NASA-TLX must be used as one of the measurements, and (4) the experiments must include multitask conditions, fulfilling the “multitasks” criteria. After applying these screening criteria, a subset of the literature was identified for further analysis.

Following the outlined methodology (Figure 2), manual screening was performed to classify the research contexts and the measurement methods employed in the studies. Initially, 102 articles were identified as focusing on algorithms, 80 were unrelated to this topic, 56 were review articles, and 79 focused on theoretical results. Among the remaining papers, 12 discussed assessment investigations, and 35 explored function development. After reviewing abstracts and titles, 33 papers remained. Of these, 9 did not utilize NASA-TLX, 2 applied NASA-TLX for prediction purposes, and 8 used alternative approaches. Ultimately, 14 articles met all inclusion criteria, as summarized in Table 1.

Table 1. The list of selected studies

N.	Citations	Experiment settings
1	(Pérez-D’Arpino et al., 2024)	Four teleoperation methods, including assisted planning, for multi-step robot manipulation.
2	(Gervasi et al., 2024)	Effect of cobot size (small vs. large) on user experience in human-robot collaboration.
3	(Korivand et al., 2024)	Q-learning and physiological data to optimize human–robot teaming in quality control tasks.
4	(Chu & Weng, 2024)	Augmented reality interfaces (hand ray, head gaze, eye gaze) for robot programming with HoloLens.
5	(Su et al., 2024)	Effects of interaction presence, complexity, and modality (button pressing, gestures, commands).
6	(Pan et al., 2024)	Shared control levels in teleoperated trajectory tasks with a robotic arm and a rhythmic tapping task.
7	(Zheng et al., 2024)	Multi-modal feedback (visual, haptic, auditory) in teleoperated robotic grasping for fragile objects.
8	(Konstant et al., 2024)	Manual, shared control, and fully automated sanding tasks with robots.
9	(Pluchino et al., 2023)	Dual-task paradigm (assembly + math) with collaborative robots for senior workers.
10	(van Dijk et al., 2023)	Human-led and robot-led (slow vs. fast-paced) assembly tasks.
11	(Panchetti et al., 2023)	Robot speed, autonomy, and interaction modalities in assembly tasks.
12	(Gervasi et al., 2023)	Learning process and collaboration factors (speed, proximity, control) in assembly tasks.
13	(Rossato et al., 2021)	Younger vs. senior workers with manual and tablet control in assembly tasks.
14	(Zhu et al., 2021)	Realistic vs. mediated force feedback in virtual valve manipulation tasks with teleoperated robots.

Due to the page limitation of the Esrel, an illustrative analysis of modalities from one study is presented as an example.

This study explored interactions under four conditions, focusing on differences in input and output modalities.

- **Condition A**: Operators handled a teleoperated robot through a 2D video feed on a screen.
- **Condition B**: The same task was performed with 3D models displayed on the screen.
- **Condition C**: Operators utilized a 3D teleautonomy interface with combined 2D and 3D perception, relying more heavily on system guidance.
- **Condition D**: Assisted planning was added to Condition C, automating certain processes.

The analysis of visual and spatial inputs across these conditions reveals notable differences. For instance, Condition B demonstrated enhanced spatial coordination due to the use of 3D perception, while Condition A relied on minimal spatial input from 2D live views. Similarly, the output differences were characterized by varying levels of operator autonomy, as shown in Table 3.

Table 2. The sample of the input modalities table from number 1 study

Experiment settings	Visual (input)	Spatial (input)
Condition A	2D on screen	Minimal spatial coordination; relies on 2D live views
Condition B	Direct Teleoperation, 3D Perception	Enhanced spatial coordination with 3D
Condition C	3D Teleautonomy Interface, 2D & 3D Perception	Less spatial input, rely on guidance more
Condition D	Same as Condition C; +Assisted Planning	NaN

Table 3. The sample of the results of output

Experiment settings	Spatial(output)
Condition A	Handling the task based on limited 2D view
Condition B	Handling the task based on enhanced 2D+3D view
Condition C	handling the task with partially autonomy (shared control)
Condition D	handling planning and execution autonomously.

Table 4. The sample of comparison NASA-TLX with different conditions

N of Experiment	NASA-TLX
Condition A	Baseline (compares with B)
Condition B	-
Condition C	Baseline (compares with D)
Condition D	-,-

The comparison between Conditions A and B, and Conditions C and D, indicates that the inclusion of enhanced perception and autonomy reduces workload, as reflected by lower NASA TLX scores from the original result in research 1. For example, transitioning from Condition A to B showed improvements due to the use of 3D visual perception. Similarly, Condition D demonstrated workload reductions when assisted planning was introduced, highlighting the positive effects of automation on operator performance. As an example, the number 1.1 is 2D-3D perception on the screen, represents on changing with operators' visual and spatial, this changing causes the NASA-TXL decreasing (-), written in the Table 5.

The remaining 13 studies were systematically with the same way of analysing methodologies, experimental conditions, and reported NASA-TLX scores as the pervious example. The overview of the construct table 5 is:

- Extracted and reported input and output modalities (e.g., visual, spatial, tactile, linguistic, auditory) from the experiment setting of each article. Linguistic modalities refer to language related information (In this article, refer to English).
- Categorized the interaction modalities based on their effect on operator workload and task performance.
- Compared NASA-TLX values across conditions to identify workload trends.

- Integrated findings from multiple studies where comparable experimental conditions were applied.

This structured approach ensures that the analysis remains systematic and reproducible, while the illustrative example offers a deeper insight into how these factors were examined.

Table 5 consolidates this information, presenting a structured comparison of how different sensory input and output modalities influenced workload results across all selected studies.

Table 5. The 14 selected research input and output modalities influenced NASA-TXL results

N	Baseline-comparison	Input	Output	WL(NASA-TXL)
1.1	2D-3D perception on screen	Visual+Spatial		-
1.2	No help-Assist planning route		spatial	-
2.1	Bigger-Smaller robot (UR10-UR3)	Visual+Spatial	Manual	+
2.2	90° /s to 270° /s Speed	Visual+Spatial	Manual	same
3.1	0.225m/s -0.075m/s	Visual+Spatial		-
3.2	No help-robot assists with holding and aligning parts	Visual+Spatial	Manual	-
4.1	Hand-Head Gaze	_	Manual	+
4.2	Hand-Eye Gaze	_	Manual	+,+
5.1	Press button-gesture	_	Manual	+
5.2	Press button-Verbal Command	_	Vocal+Linguistic	+,+
6	No help-trajectory tracking assistant	_	Spatial	-
7.1	Fixed visual-Dynamic visual	Visual+Spatial	Spatial	-
7.2	Fixed visual-Fixed visual + haptic feedback	Tactile	_	-
7.3	Dynamic visual-Fixed visual + haptic feedback	Visual+Spatial+tactile	_	+
7.4	Dynamic visual feedback-Dynamic visual + auditory feedback	Auditory	_	-
7.5	Dynamic visual-Dynamic visual + haptic feedback	Tactile	_	-
7.6	Dynamic visual+haptic-Three modals	Auditory	_	-
7.7	Dynamic visual-Three modals	Spatial+tactile	_	-,-
8	Manual sanding-Joystick controller	Spatial+tactile	Manual +spatial	-
9	Single Task-calculating	Linguistic	_	+
10.1	Human lead speed-slower robot	spatial	Manual	-
10.2	Human lead speed-Faster robot	spatial	Manual	+
11.1	Normal speed +press button-+gesture command	spatial	Manual	-
11.2	Normal speed +press button-mixed gesture and press command	Spatial	Manual	-,-
12.1	30°/s-90°/s.	Visual+Spatial	Manual	+
12.2	30°/s-270°/s.	Visual+Spatial	Manual	+,+
12.3	90°/s-270°/s	Visual+Spatial	Manual	+
13	physical touch-pendant/tablet control	Visual	Manual	-
14	Without Force Feedback-with	Tactile	_	-

3. Results

Figure 3 presents a filled framework that clusters interaction modalities based on insights from the 14 selected studies. The approach was categorizing modalities according to their impact on cognitive workload, type of sensory engagement, and functional role in human-robot collaboration described in the methodology chapter.

This study reveals key insights into the influence of different interaction modalities on workload in human-robot collaboration. Linguistic-related interactions, whether input or output, consistently increase cognitive demands, highlighting the need for system designs that minimize their impact. Conversely, tactile assistance demonstrates a clear positive effect on workload, emphasizing the value of incorporating tactile feedback to enhance operator efficiency.

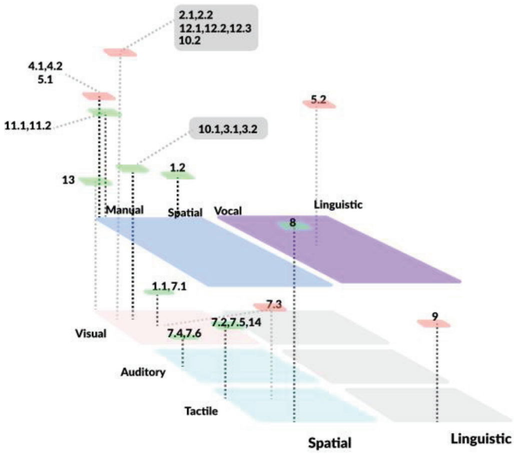

Fig. 3. Protocol for searching and screening

Input-assist interactions generally reduce workload, with scenarios like 7.3 showing how limited visual feedback can hinder performance. Optimizing these interactions, particularly within the input-assist zones identified in the proposed framework, offers significant potential for workload management. Environmental factors, such as robot size and speed (e.g., experiments 2.1, 2.2, 12.1, 12.3, 10.2), also play a crucial role in shaping visual and spatial workload. Experiments comparing fixed and flexible responses (e.g., 11.1, 11.2 vs. 4.1, 4.2, 5.2) further highlight the importance of operator autonomy in reducing cognitive demands.

4. Conclusion and discussion

Current studies on robotic interaction assist predominantly focus on visual and spatial modalities, leaving opportunities to explore alternatives such as auditory and tactile interactions, as well as their combinations. These unexplored areas represent valuable margins in the proposed framework that warrant further investigation to improve operator support in manufacturing. However, the results indicate that linguistic modalities consistently contribute to increased cognitive load. This may be attributed to the fact that linguistic processing is a learned cognitive function rather than an instinctive response, requiring greater mental effort for interpretation and execution. Despite this cognitive demand, linguistic communication remains essential in complex industrial settings where precise information exchange is critical for both operational efficiency and adherence to safety standards (ISO 12100, ISO 14121-1, ISO 14121-2). Given these constraints, future research should prioritize the optimization of linguistic interactions, exploring strategies to mitigate cognitive overload while ensuring effective and compliant information transfer in human-robot collaboration.

By applying this framework, managers and system designers can better balance cognitive and physical demands. Practical steps, such as enhancing tactile assistance, optimizing input-assist interactions, and promoting operator autonomy, align with Industry 5.0's human-centric principles and enable workers to adapt more effectively to complex environments.

Despite its contributions, this study acknowledges limitations. While NASA-TLX is an effective tool for measuring workload, it may not fully capture the nuances of linguistic and multi-modal interactions. Future research should integrate complementary metrics, such as heart rate variability (HRV) and galvanic skin response (GSR), to provide a more comprehensive evaluation. Additionally, demographic factors influencing workload under the same modalities should be examined to enhance the framework's applicability across diverse contexts.

In conclusion, this study advances the understanding of human-robot collaboration by refining cognitive ergonomics within input and output modalities. By addressing critical workload factors, such as linguistic tasks, tactile feedback, and operator autonomy, it offers actionable strategies for improving human-robot interactions and enhancing operator performance in Industry 5.0 settings.

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