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Support or Overload? Cognitive Ergonomics in Human-Robot Application

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The introduction of collaborative robots and Human-Robot Collaboration (HRC) systems in industrial contexts can sustain or even increase productivity while improving workers' well-being by reducing physical strain and assisting or replacing humans in repetitive or non-ergonomic tasks. Attention to safety requirements by design (e.g., sensors, force control) has increased over time, as an essential element of HRC. However, while safe and healthy collaboration should depend on both physical and cognitive comfort, HRC might induce mental stress and cognitive workload, ultimately affecting workforce health. These aspects, as well as their consequences for the workforce, have not yet been fully systematized, resulting in unclear guidance for establishing effective HRC in industrial contexts. Hence, this preliminary literature review aims to analyze the literature on the cognitive ergonomics of HRC systems across diverse industrial applications, seeking to answer the following research question: What are the main insights provided by the extant literature on cognitive ergonomics in HRC in industrial contexts? What are the recent developments identified within this domain, and how can they inform future research directions? As a result, recurring trends and promising future research directions are outlined. Analyzed articles underscore the importance of multimodal measurements to capture the intricate dynamics of human-robot collaborative settings, as well as the need to consider a broader set of indicators related to experience-level outcomes of HRC (e.g., affective well-being). Increasing attention is given to systems that draw on psychophysiological information to adapt in real-time collaboration dynamics (e.g., the cobot's pace) to individual variability and preferences.

Keywords: Cognitive Ergonomics, Human-Robot Collaboration, Manufacturing, Occupational Health, Literature Review, Industry 5.0.

1. Introduction

The paradigm of human–robot collaboration (HRC) has attracted growing interest over the last decade, as the joint interaction between humans and robots in the workplace makes it possible to leverage the strengths of both partners, combining human capabilities and soft skills with the efficiency and precision of industrial automation (La Fata et al., 2025). In HRC contexts, humans and robots work together in a shared workspace, relieving workers of the physical strain of repetitive activities and allowing them to focus on more complex, value-added tasks, thereby maintaining or enhancing overall efficiency and productivity (Giallanza et al., 2024). The robotic systems employed in these settings, commonly referred to as "collaborative robots" or "cobots", are specifically designed to enable direct interaction with their human counterparts. Unlike traditional industrial robots, which require strict physical separation and protective cages, cobots are characterized by high flexibility and adaptability to diverse production needs: their design and ease of programming allow them to be easily relocated and reprogrammed, making them suitable for dynamic environments and overcoming the limited versatility of conventional industrial robots (Villani et al., 2018). From this perspective, using cobots to complement human capabilities in industrial tasks such as assembly or pick-and-place operations is often more advantageous than full automation, which would require continuous and costly engineering efforts (Vicentini, 2021). Given the proximity between humans and robots in collaborative settings, safety is a primary concern in research and technical standards, which aim to mitigate mechanical hazards (e.g., collisions or pinch points) arising from intentional or unintentional human-robot contact during task execution. For instance, ISO/TS 15066:2016 (currently under review) specifies methods for collaborative operation (safety-rated monitored stop, hand guiding, speed and separation monitoring, and power and force limiting), defined as "safety features". Accordingly, a substantial body of research has focused on safety aspects, with particular interest in topics such as collision avoidance, contact detection, and mitigation (Gualtieri et al., 2021; Giallanza et al., 2024).

While these contributions have been fundamental in enabling physically safe collaboration, uniquely targeting mechanical risk reduction does not fully account for the broader conditions required for a safe and healthy collaboration between humans and robots. Although HRC can reduce exposure to repetitive and physically demanding tasks, it might also introduce new, often overlooked cognitive risks given the robot's proximity and the absence of physical barriers (Giallanza et al., 2024). Cognitively demanding work environments can adversely affect system efficiency and overall productivity while simultaneously exposing operators to cognitive failure or overload, with potential consequences for occupational health and safety (Gualtieri et al., 2022). From this perspective, investigating cognitive ergonomics (CE) factors (such as mental workload) in HRC contexts is essential to inform the design and development of collaborative systems that are not only physically safe, but also capable of supporting operator well-being beyond a purely productivity-driven rationale, in line with the Industry 5.0 paradigm that stress the human-centric role in industry and the importance of technology that adapts to the workers, not the other way around (European Commission, 2021).

Therefore, this review aims to give a comprehensive understanding of the current knowledge on cognitive ergonomics in HRC in industrial contexts, answering the following research questions:

What are the main insights provided by the extant literature about CE in HRC in industrial contexts? What are the recent developments identified within this domain, and how can they inform future research directions?

To this end, Section 2 outlines the review's methodological approach and introduces the key concepts that structure the analysis. Section 3 presents the identified relevant literature, while Section 4 discusses emerging trends and promising avenues for future research; finally, Section 5 concludes.

2. Methods

The literature review was conducted using the Scopus database. The focus was on both theoretical and empirical papers addressing HRC in industrial settings (e.g., assembly, pick-and-place, handover), including laboratory-based experiments designed to approximate manufacturing tasks. Papers were included if they addressed only cognitive or both cognitive and physical ergonomics, in the sense that they were empirically measured (through subjective, behavioral, or physiological methods) or discussed in literature reviews. The focus was on journal papers in English (per Scopus filters), and no time span was set. Articles focused only on technical aspects of cobots, as well as those addressing only physical ergonomics, were excluded. Studies focusing on non-industrial domains or other classes of robots, such as surgical robotics, service and social robotics, were excluded. Retrieved records were screened based on title and abstract, followed by full-text assessment to confirm eligibility.

The search strategy combined keywords related to HRC and CE. HRC is generally defined as collaboration between a human and a robot in a shared workspace, not necessarily continuously/synchronously (Vicentini, 2021). Although the term "*collaboration*" is the predominant wording in technical standards, academic literature also uses related terms such as "*cooperation*" and "*coexistence*" to describe varying degrees of collaborative action between humans and robots (Weiss et al. 2021), and to avoid missing relevant studies due to terminology differences, these terms were also included. CE is a domain of ergonomics, concerned with how system characteristics interact with human cognitive capabilities and limitations, with emphasis on mental processes such as perception, attention, decision-making, learning, and memory (Hollnagel, 1997). In this context, mental workload is one of the most extensively investigated constructs (European Agency for Safety and Health at Work, 2023). Despite its widespread use, mental workload lacks a universally accepted definition. It is generally understood as the amount of mental effort required to perform a task under given conditions (Longo et al. 2022). Different synonyms were therefore employed in combination to capture the nuances of this concept, such as mental "*workload*", "*demand*", "*effort*", "*load*", and "*fatigue*", together with "*cognitive ergonomic**".

3. Results

This section synthesizes theoretical and empirical evidence identified through the review, focusing on how recent literature conceptualizes and addresses CE aspects in HRC industrial scenarios.

A literature review by De Nobile et al. (2024) focused on methodologies for assessing human factors in HRC environments across psychological, cognitive, and physical domains, showing that assessment practices increasingly combine subjective (e.g., questionnaire) and non-subjective methods. While questionnaires remain the most prevalent, a growing trend is to integrate them to complement each other and obtain a comprehensive understanding of dynamics in HRC settings. Subjective tools like the NASA Task Load Index (TLX) are particularly suited to capturing operators' perceptions, feelings, and attitudes toward the HRC scenario, especially for constructs such as acceptance, trust, and usability, which are primarily addressed through questionnaires. Conversely, objective methods (i.e., methods that provide physiological and physical data) offer continuous indicators of real-time responses to cognitive and psychophysiological demands, typically leveraging cardiovascular, electrodermal, and neurological activity. In line with this methodological rationale, Borghi et al. (2025) evaluated operator stress during cobot programming for pick-and-place tasks with increasing complexity, using a multimodal approach that combines physiological signals – electroencephalogram (EEG), electrocardiogram (ECG), and galvanic skin response (GSR), facial-expression emotion recognition, and a subjective questionnaire (NASA-TLX). Findings showed strong agreement between subjective ratings and several physiological indicators, supporting the added accuracy of combining metrics. The study also confirmed that physiological responses generally track task complexity (i.e., more complex tasks lead to higher stress) but highlighted substantial inter-individual variability in stress-related responses and perceived mental demand. Interestingly, elevated stress indicators were observed not only for more complex tasks, but also in the early stage, suggesting initial anxiety/distrust when approaching the cobot. The findings of Gervasi et al. (2025) confirmed this latter aspect, finding that mental demand is typically higher at the start of work periods (possibly due to a learning/familiarization effect) and decreases as operators adapt to the repetitive process. In their study, they discussed the potential of eye-tracking technology in addressing CE (specifically, mental workload) in long session manufacturing environments (i.e., assembly task divided in morning and afternoon shift), finding that different eye-tracking metrics appear sensitive to different workload-related phenomena (e.g., "number of fixations" for learning-related resource investment vs “average pupil dilatation” for fatigue-related strain), supporting the need to interpret cognitive states through a combination of metrics rather than a single indicator, and finding consistency with the subjective response related to mental demand (NASA-TLX questionnaire).

Gervasi et al. (2024) focused on monitoring stress, cognitive workload, and fatigue in manually and cobot-supported long-duration assembly tasks, using electrodermal activity (EDA) and heart-rate variability (HRV) collected throughout the shift and relating these signals to process-failure indicators (e.g., incorrect part positioning). The comparison showed that the cobot provides implicit cognitive support, especially in the early phase of the shift: by presenting/holding components consistently, the cobot helps operators remember assembly steps and reduces process failures, with the most apparent benefit observed in reducing incorrect part positioning (a recurrent difficulty in the manual condition). As the shift progressed, however, cognitive workload increased in HRC settings, and the authors linked this trend to accumulated fatigue and slight frustration: several participants reported that, once they had become familiar with the task, they wished the cobot operated faster to match their improved pace. This feedback supports the need for HRC configurations that can be customized to operators’ needs, so that the benefits of cobot support are maintained over prolonged work periods.

Orlando et al. (2025) examined operators’ cognitive and psychophysiological responses during HRC in industrial settings (i.e., an assembly task) by jointly assessing operators’ mental workload, fatigue, stress, and affective well-being, using multiple physiological (HRV and pupillometry) and subjective measures. Although interrelated, the authors highlighted conceptual differences among these dimensions: mental workload is understood as the cognitive demands imposed by the task, fatigue as the progressive depletion of cognitive/physical resources with time on task, and stress as a broader psychophysiological reaction when the situation is appraised as challenging. On this basis, the study emphasized the value of multidimensional and multimodal assessment over workload-only approaches to capture contextual and individual differences (e.g., high workload does not necessarily imply high fatigue, and their relationship may strengthen with prolonged exposure).

In a review paper, Lu et al. (2022) synthesized evidence on factors that can affect mental stress and safety awareness during HRC, along with related measurement approaches. They reported consistent associations between operators’ stress/awareness and robot-related features, including size, moving speed, and trajectory. In parallel, the authors described assessments that typically combine direct measures with indirect physiological and performance-based measures, noting that multimethod approaches help mitigate limitations associated with single-channel measurement and individual variability. Notably, the authors stressed the importance of “bidirectionality” in information exchange: not only do humans respond to robot actions, but robots can, in principle, respond to human behavior and inferred psychological states (e.g., by reducing speed when higher mental stress is detected). Technological advances in physiological measurement can enable real-time detection and information processing by the cobot. This aspect was addressed by Morandini et al. (2025), who provided a systematic scoping review on adaptive cobots, i.e., collaborative robots that modify their behavior in real time based on workers’ psychological states. The review showed that most adaptive approaches target cognitive states, especially workload, attention, and situational awareness. In contrast, adaptation to emotional states (e.g., stress, fatigue, discrete emotions) is less frequently addressed and is often considered more challenging to operationalize reliably in real time. Cobots infer these states mainly through physiological and behavioral cues (e.g., HRV, EDA, gaze/eye metrics), and implement adaptations such as speed modulation, task reallocation, changes in autonomy/assistance, and interaction support that generally offer a positive effect in terms of collaboration fluency, cognitive workload management, and operational performance.

The effects of the cobot’s motion features are further addressed in the literature. Lu et al. (2024) investigated how robot motion characteristics (approach direction, speed, and movement trajectories) affect workers' mental stress during handover tasks, using a combination of self-report and objective measures. Consistent with other studies (e.g., Borghi et al., 2025; Orlando et al., 2025; Gervasi et al., 2025), the findings indicated that physiological and subjective measures provide complementary information: notably, some interaction effects among motion factors are observed mainly in subjective ratings rather than in physiological signals, suggesting that self-reports can be particularly sensitive to nuanced perceptual dimensions such as surprise and predictability of the cobot movements. Moreover, the study indicated that motion parameters should be considered jointly, as their effects can depend on one another. Approaches from the side are associated with higher perceived stress and lower predictability than approaches from the front across speed conditions, supporting the practical recommendation that the end effector should approach workers within their field of view; more generally, lower stress is observed when the cobot approaches at lower speeds. Similarly, Zhang et al. (2025) investigated the effect of two stressors, robot speed and task time, on mental workload and stress in extended exposure to HRC settings. Workload and stress were assessed through subjective ratings (NASA-TLX) and performance (n-back). At the same time, facial-feature changes were explored as a non-intrusive behavioral signal for distinguishing task conditions, an approach still relatively underused in industrial HRC compared with other physiological methodologies. Their finding aligned with Lu et al. (2024), as the operators experienced higher stress and mental workload levels in high-speed settings; moreover, stress/workload indicators increased toward the end of the task, plausibly reflecting the accumulation of sustained attentional and coordination demands over prolonged exposure, rather than primarily early-stage learning or initial familiarization effects, as found by Borghi et al. (2025) and Gervasi et al. (2025).

Lagomarsino et al. (2023) proposed an online framework to assess cognitive load during the HRC assembly task with different interaction modalities. The framework operationalizes cognitive load through complementary dimensions that extract multiple indicators from an RGB-D camera, capturing mental effort, stress-related behavioral cues (e.g., hyperactivity/self-touching as body-language proxies), and trust-related behaviors toward the assistant (e.g., attention allocation and wariness patterns). Results indicated that greater transparency and feedback (i.e., a clearer understanding of what the robot is doing) are associated with lower mental effort and stress and with more favorable trust development, with the most substantial differences emerging among HRC-naïve participants, who tended to experience automation as more demanding when transparency is limited. Moreover, in line with the concept of bidirectionality emphasized by Lu et al. (2022), this kind of architecture can enable "closed loop" adaptation, where online estimates of mental effort/stress/trust can inform real-time adjustments to the robot's control strategy to better match operator needs. In the same vein, Lagomarsino et al. (2025) proposed a human-in-the-loop framework to optimize the adjustment of the cobot's proximity level and reactive behavior (i.e., path and timing adaptation) based on monitoring human attention and psychophysical state. The approach combined camera-based monitoring of the operator's attention/awareness and mental effort with physiological and behavioral indicators (i.e., HRV and movement cues) to dynamically scale safety-related distances and trigger online path adaptation (i.e., avoiding entry into a "cognitive-grounded" safety zone when the operator is distracted or cognitively strained). In parallel, the framework allows timing adaptation through an online decision module that selects among trajectory options to trade off execution speed and motion smoothness in response to detected stress, thereby modulating the collaboration pace without introducing abrupt or unpredictable robot behavior. The proposed framework, validated through an experimental case study, can help operationalize cognitive/psychophysical factors into actionable motion planning that addresses individual variability, overcoming the limitation of fixed (or "static") speed that can lead to overly cautious behavior.

4. Discussion

The field of CE in HRC is attracting increasing attention, and this preliminary analysis has identified trends that point to possible avenues for future research, which are discussed in the following sections and summarized in Table 1.

4.1. *Multimodal assessment*

A consistent methodological trend is the shift from single measures toward integrated assessment approaches that combine subjective and physiological/behavioral data. Borghi et al. (2025) show that subjective ratings and physiological signals often converge but also reveal variability that would be poorly captured by one channel alone; similarly, Orlando et al. (2025) treat workload, fatigue, and stress as related but non-equivalent dimensions, arguing that a single construct (e.g., workload) cannot fully address cognitive complexity in HRC. Future research should leverage multimodal assessment as not only a matter of improving “accuracy”, but also of extending construct coverage: physiological signals can provide continuous markers of cognitive and psychophysiological activation, while subjective tools can capture operators’ appraisals of the collaboration, such as perceived predictability, comfort/safety, control, usability, and trust. In practice, this is also reflected in the increasing use of additional constructs to capture the nuances of HRC dynamics (Section 4.2).

4.2. *Broadening constructs for effective understanding of HRC*

Many recent contributions in HRC in industrial settings adopt a CE perspective focused primarily on quantifying mental workload, often treated as the primary indicator of the cognitive sustainability of collaboration – e.g., Gervasi et al. (2025); Lagomarsino et al. (2023). Nevertheless, a further emerging area concerns the analysis of affective and emotional responses to HRC. Even when not treated as the central focus of analysis, affective appraisals can be captured through subjective instruments that assess operators’ perceived emotional state in the interaction. For instance, Orlando et al. (2025) include self-report dimensions aligned with affective appraisal (e.g., valence or arousal). In future research, this could help clarify how cognitive demand translates into experience-level outcomes such as discomfort or trust and provide complementary information to workload indicators; for instance, two HRC configurations may produce similar workloads but differ substantially in perceived comfort or emotional strain.

Table 1. Future research directions

Heading	Future research direction
Multimodal assessment	Address cognitive aspects through multimodal measurement (i.e., subjective + objective measures) to increase accuracy and capture nuances of HRC dynamics.
Broadening constructs for effective understanding of HRC	Include the assessment of experience-level outcomes of HRC, related to (e.g.) operators’ affective well-being to complement cognitive workload indicators.
Bidirectional and adaptive HRC	Focus on psychologically informed HRC settings, where the use of psychophysiological measurements informs real-time adaptation of the cobot features (e.g., peace) in line with operators’ response or preference.

4.3. *Bidirectional and adaptive HRC*

A particularly relevant development is the emergence of closed-loop, psychologically informed HRC settings, where estimates of workload, attention, or stress are used as inputs to adapt collaboration dynamics. Lu et al. (2022) explicitly discuss the bidirectional nature of interaction: humans adapt to robots, but robots can also adjust to human states. Morandini et al. (2025) showed that most adaptive approaches currently focus on cognitive states (workload, attention, situational awareness) rather than emotional states, likely because cognitive indicators are more readily operationalized with existing technology. These contributions shift CE from “a posteriori” evaluation tool to a design principle for dynamic well-being: adapting speed, trajectory, proximity, transparency, or task allocation in response to operator state. The individual variability encountered in HRC settings, e.g., Lagomarsino et al. (2023), Gervasi et al. (2023), calls for more adaptive collaboration settings that can meet individual differences, as the comfort of interaction with the cobots (e.g., speed or trajectory) may vary significantly based on previous experience or individual cognitive capabilities.

5. Conclusion and Limitations

As HRC becomes increasingly prevalent in industrial applications, ensuring that operators can work with cobots in a state of cognitive comfort is essential for both effective deployment of this technology and workforce well-being. In this context, CE is a fundamental target to ensure the sustainability of collaborative robotics; accordingly, future research can build on the evidence synthesized in this preliminary review to prioritize and further investigate the most relevant emerging directions in the field.

The study presents some limitations. First, the review is in its preliminary phase. It will be expanded by including more empirical and theoretical evidence, enabling a more comprehensive synthesis and a more structured identification of research directions. Furthermore, the focus on industrial applications strengthens contextual relevance but may exclude transferable insights from other domains where collaborative robotics is rapidly advancing, such as healthcare (e.g., robotics for surgery). Therefore, research from different fields might offer insights with external validity that benefit industry-related applications.

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