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Review Article

Collaborative Robots Adapting Their Behavior Based on Workers' Psychological States: A Systematic Scoping Review

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Integrating collaborative robots (cobots) in work environments is advancing rapidly, with growing attention to designing systems that can effectively collaborate with humans. A key aspect of this effort is enhancing cobots' adaptability, that is, their ability to adjust behavior in real time based on workers' needs and characteristics, particularly their psychological states. Despite increasing research, a synthesis of the most considered psychological states and the corresponding adaptation mechanisms is still lacking. This review examines recent experimental evidence on cobots which modify their behavior in response to workers' psychological states and evaluates how these adaptations influence human–robot collaboration outcomes. Following preregistration on PROSPERO, this study adhered to PRISMA-P guidelines to select 23 studies focusing on cobots' adaptation mechanisms and their impact on task performance and worker well-being. The findings reveal that most adaptations target cognitive states, particularly workload, attention, and situational awareness, reflecting a strong research emphasis on optimizing decision-making and efficiency. Emotional adaptation has been explored to a lesser extent, while real-time adjustments based on motion intention are gaining traction in movement coordination tasks. Cobots primarily rely on physiological and behavioral signals—such as heart rate variability, electrodermal activity, and gaze fixation—to infer workers' psychological states. Various adaptation strategies, including task reallocation and speed modulation, demonstrate measurable improvements in collaboration fluency, cognitive load management, and operational performance. This review highlights the critical role of psychology in robotics research, promoting multidisciplinary collaboration to develop adaptive cobots that enhance both productivity and worker well-being.

Keywords: adaptiveness; cobot; human–robot collaboration; psychological states; robot

1. Introduction

Driven by advancements in automation, machine learning, and artificial intelligence, robotic systems are transforming many work sectors, including manufacturing, logistics, agriculture, and healthcare [1]. In just a few years, their integration into work environments has evolved rapidly, shifting from rigid, preprogrammed automation to more flexible and interactive systems capable of collaborating with human workers [2]. Human–robot collaboration (HRC) has emerged as a key paradigm in this context, referring to scenarios where humans and robots work together on shared tasks, leveraging their strengths to improve efficiency, safety, and worker well-being [3]. Unlike traditional automation, where robots operate independently or in isolated environments, HRC emphasizes dynamic interaction, real-time coordination, and mutual adaptation, ultimately enhancing task execution and the user experience [4–6].

A recent systematic review by Hopko et al. [7] has emphasized the complexity of human factors in shared-space HRC, highlighting the bidirectional dynamics and continuous adaptation processes that occur when humans and robots operate in close physical proximity.

Conversely, other recent studies have introduced approaches that extend the HRC concept beyond traditional shared physical workspaces. These include remote interaction and teleoperation, which facilitate collaboration when physical proximity is not possible or advisable [8, 9]. Additionally, multirobot systems expand collaboration beyond one-to-one interactions to encompass scenarios involving human operators collaborating with multiple robotic agents [10].

A fundamental aspect of HRC's progress is robotic adaptability, meaning a robotic system's ability to dynamically modify its behavior in real time in response to external conditions or changing human needs [11]. Adaptive technologies have the potential to enhance trust and efficiency in human–robot interactions, making them a crucial element in the development of next-generation intelligent systems [12].

The relevance of adaptive robotics is increasingly emphasized in international policy and regulatory frameworks, which promote the need to align emerging technologies with human needs and values. The European Agency for Occupational Safety and Health published a set of recommendations about how to prioritize safety and address social and ethical considerations, advocating for technological development transparency while fostering positive human–machine interactions. To achieve these objectives, the agency strongly supports the integration of human-centered disciplines (such as psychology and social sciences) into robotics research [13]. Moreover, in the document titled "ERA Industrial Technologies Roadmap on Human-Centric Research and Innovation for the Manufacturing Sector," the European Commission prioritizes the need to develop human-centric approaches in industry using collaborative and smart robots, leading to empowered workers with optimized, trustful user experiences and effective collaborative task performance. Additionally, it focuses on developing socially adaptive robots through industry and industry cluster research, as well as integrating ergonomics in the design of collaborative robots to make HRC safer and healthier [14]. Similarly, in the United States, private sector initiatives and regulatory discussions are aimed at developing guidelines for the implementation of robotic systems that enhance productivity while ensuring safe, transparent, and reliable interactions across multiple domains, including industry, healthcare, and public services [15].

Emerging research on robotic adaptability is primarily focused on three areas. The first concerns ergonomic adaptation, in which robots modify their physical behavior based on users' posture, effort levels, or workload to improve safety and prevent strain-related injuries. In this context, ergonomic adaptation is achieved through robot monitoring systems, such as wearable sensors and vision technologies, which analyze users' posture and adjust the robot's behavior accordingly. Studies in this field demonstrate that cobots can adjust to more ergonomic configurations, improving the work experience and reducing the risk of injury [16]. Furthermore, research such as that by Yazdani et al. [17] and Makrini et al. [18] shows that AI-based approaches can provide differentiated ergonomic models, optimizing individual and diverse physical interactions in HRC.

The second research direction explores affective adaptation in social robotics, particularly in healthcare and education, where robots recognize and respond to patients' or students' emotional states to enhance engagement and support therapy. A study by Šabanović et al. [19] demonstrates how using robots in group therapy for elderly patients with dementia can encourage social interaction between participants and the machine, creating a more engaging environment. In the educational context, affective robotics proves helpful in supporting children with autism spectrum disorders. Robots in this setting are designed to interact with individuals with autistic spectrum disorders, express emotions, and serve as therapeutic tools to improve social interaction [20, 21].

The third emerging research direction concerns the role of workers' psychological states in guiding robotic adaptability in workplace environments [22]. This area is gaining increasing attention, as understanding how cobots can dynamically adjust their behavior in response to cognitive workload, stress, engagement, or attention levels could significantly enhance HRC, fostering trust and improving worker satisfaction and well-being [23]. While previous research in work settings has primarily focused on ergonomic adaptation, studies investigating how robots adjust their behavior in real time based on workers' psychological states are still in their early stages. As a result, there is currently no literature review synthesizing the available evidence on this topic, making it difficult to assess the state of knowledge, identify existing gaps, and define future research directions.

This systematic scoping review is aimed at filling this gap by synthesizing the literature on adaptive robots that modify their behavior in response to human psychological states during collaborative work tasks. The objective is not only to systematize emerging knowledge on this topic but also to assess how these adaptive systems enhance HRC by optimizing task performance while promoting worker well-being through stress reduction, improved comfort, and increased satisfaction. In addition to providing a structured synthesis of knowledge in the field, this work highlights the growing importance of integrating psychological insights into the design of new technologies.

2. Method

A scoping review was conducted to gather evidence on cobots' real-time adaptation to workers' psychological states and their influence on HRC. This method was chosen for its effectiveness in mapping and synthesizing existing knowledge while identifying research gaps that warrant further investigation. The review followed the five-step framework proposed by Arksey and O'Malley [24], ensuring a systematic and comprehensive literature examination. An additional step involving a risk-of-bias and quality assessment was introduced to increase the reliability of the included studies. The whole process was guided by PRISMA-P principles [25], structuring study selection and data extraction.

The review protocol is registered on PROSPERO under the number CRD42025648417.

Step 1: Identification of the research question

This study was aimed at reviewing the literature on cobots' real-time adaptation to workers' psychological states. The primary objective was to identify the psychological states incorporated into adaptive cobot systems and assess their effectiveness in enhancing HRC based on existing evidence.

A secondary objective was to highlight the role of psychology-driven adaptive mechanisms in optimizing HRC, with potential benefits for task performance and worker well-being across various sectors. More broadly, the study sought to raise awareness within the research community and among practitioners about the promising contribution of psychological insights into cobot design. Ultimately, this research is aimed at fostering interdisciplinary advancements between psychology and STEM to enhance HRC.

Step 2: Identification of relevant studies

The identification of relevant studies followed a structured approach. Searches were conducted across academic databases, including Scopus, Web of Science, and SciSpace. A snowballing technique was employed, incorporating backward citation searching from the reference lists of key studies and forward citation tracking to identify additional relevant literature. The search strategy was initially developed for Scopus, using predefined keywords related to cobots, HRC, psychological states and cues, and adaptation mechanisms. Boolean operators and wildcard symbols were applied to refine search results and improve retrieval precision.

The search syntax for Scopus was as follows: *TITLE-ABS-KEY ("robot" OR "collaborative robot" OR cobot OR "human-robot collaboration" OR "HRC" OR "human-robot team∗" OR "human-robot interaction" OR "HRI") AND TITLE-ABS-KEY ("adaptive" OR "adaptation" OR "adjustment" OR "dynamic behav" OR "flex behav∗" OR "flexibil∗") AND TITLE-ABS-KEY ("psych∗ state∗" OR "cognit∗ state∗" OR "emotion∗ state∗" OR "mental state∗" OR "mind state∗")∗∗.*

This strategy was adapted for Web of Science and SciSpace to align with their specific indexing structures and search functionalities while maintaining consistency in retrieving relevant studies.

The initial search yielded 1089 studies. After removing duplicates ($n = 482$), 607 articles remained for title and abstract screening. At this stage, 490 studies were excluded based on relevance and eligibility criteria, leaving 117 full-text articles for detailed assessment. Following a full-text review, 28 studies met the inclusion criteria, and 23 were ultimately included in the final synthesis.

Step 3: Study selection

This review included only experimental studies published in peer-reviewed journals or peer-reviewed conference proceedings to ensure a focus on data-driven research. Reviews, book chapters, books, editorials, and theoretical papers were excluded to prioritize studies with rigorous methodologies and reinforce the reliability of the findings by emphasizing empirical evidence over theoretical discussions.

To maintain alignment with the review's objective, only studies analyzing cobots' real-time adaptation to workers' psychological states in the context of HRC were included. This also applied to studies in which collaboration occurred through configurations such as teleoperation, multirobot systems, or assistive scenarios, provided they involved collaborative task execution between humans and robots.

Articles were required to provide empirical evidence illustrating the adaptation mechanisms of cobots and their impact on task performance and worker well-being. Studies were excluded if they did not focus on real-time adaptation, if adaptation was not based on human psychological states, or if they lacked experimental testing. Additional exclusions were applied to studies that examined collaboration involving individuals other than workers or lacked a clearly defined working context. Further, to ensure the reliability of the included studies, articles that had been retracted from publication, were published in non-English language, or were published before the year 2000 were also excluded. The overall study selection process is summarized in Figure 1.

Step 4: Risk of bias and study quality assessment

The risk of bias and quality of the included studies were independently assessed by two investigators using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Quasiexperimental Studies [26]. This tool was selected because it offers a structured and comprehensive approach to evaluating experimental and quasiexperimental designs. The checklist assesses key aspects of study quality, including causality, participant similarity, intervention comparability, control group presence, pre–post measurement, follow-up completeness, measurement consistency, outcome reliability, and statistical appropriateness. Each domain was rated to determine the level of bias, categorized as low, unclear, or high risk. Two investigators conducted independent evaluations, and any discrepancies in scoring were resolved through discussion to ensure consistency and reliability in the assessment process.

Step 5: Charting the data

The extracted information for each included study was organized in a table summarizing the robot configurations, working sectors, collaborative tasks, psychological states and cues, assessment tools, adaptation mechanisms, and their impact on HRC. The table is provided later in the Results section.

Step 6: Collating, summarizing, and reporting the results

This review adopted a categorization approach informed by established psychological and human factors literature to classify the data extracted from the included studies. First, psychological states were organized into three main categories: cognitive states, emotional states, and motion behaviors. The categorization of each state, along with its definition, is presented below.

2.1. Cognitive States

- Attention governs the selection and focus on relevant stimuli, determining how mental resources are filtered, prioritized, and allocated during task execution [27, 28].
- Cognitive workload refers to the mental processing resources required to perform a task, directly influencing information-processing capacity, memory load, and problem-solving functions [29–31].
- Cognitive conflict arises when individuals encounter competing or contradictory information, engaging

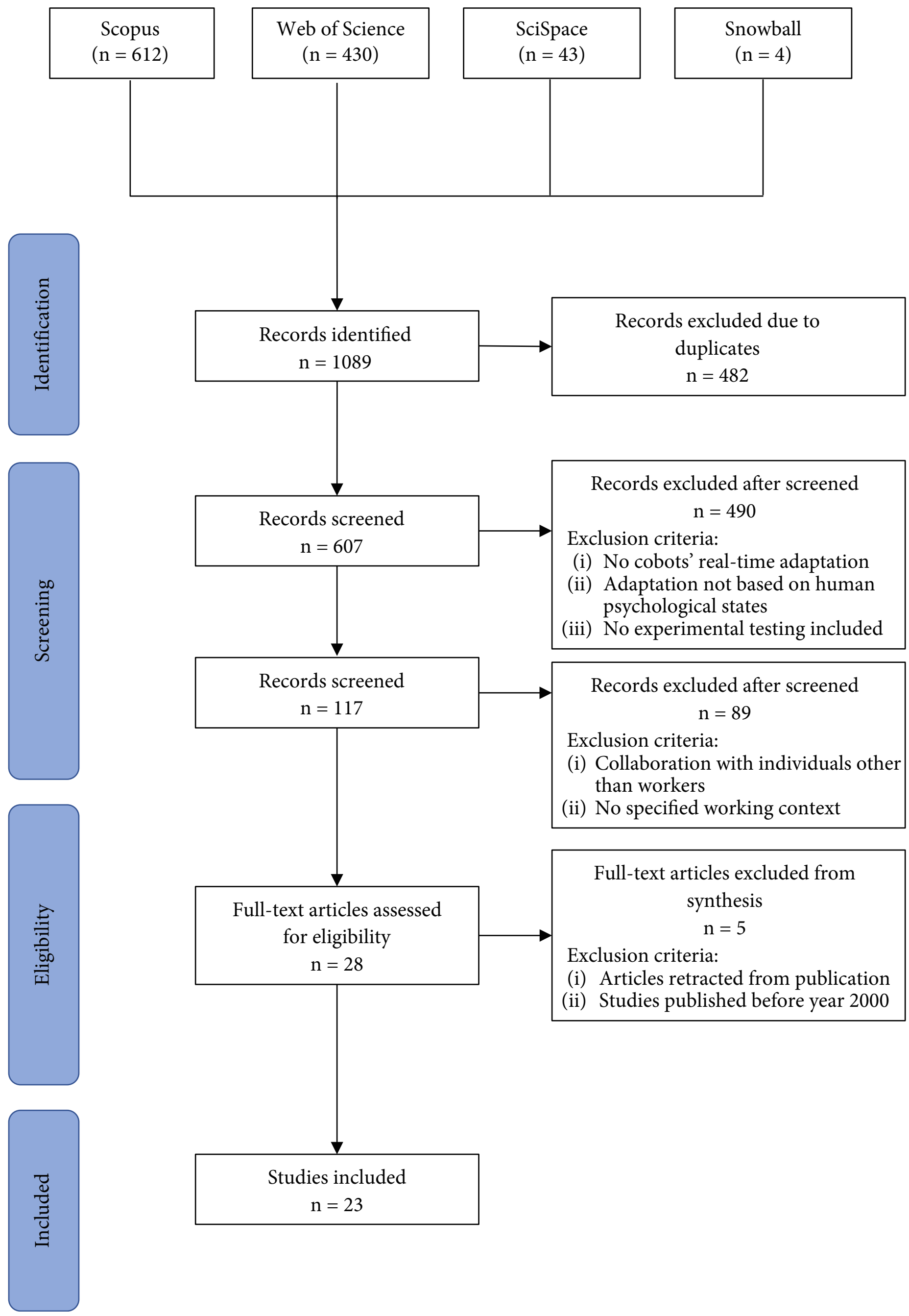

Figure 1: PRISMA flowchart summarizing the study selection process.

executive control processes essential for conflict resolution and task adaptation [32].

- Situational awareness involves the perception, comprehension, and projection of environmental elements, supporting real-time decision-making through active mental representation and information integration [27].

- Task engagement reflects sustained cognitive involvement and motivation in a task, encompassing attentional and effort-related processes that are crucial for maintaining performance [33].

2.2. Emotional States

- Discrete emotions include happiness, sadness, anger, surprise, fear, and disgust; these primary affective responses are regulated by neural and endocrine systems, shaping behavioral tendencies and interaction dynamics [34].

- Fatigue is a psychological state characterized by diminished energy and reduced cognitive efficiency, affecting mood, alertness, and emotional resilience during task execution [35].

- Self-confidence is the perception of one's competence and likelihood of success in a given task, influencing emotional regulation, perceived self-efficacy, and motivation levels [36].
- Stress is an affective response to perceived external pressure or challenge, regulated by the autonomic nervous system and impacting emotional reactivity and arousal [35, 37].

2.3. Behavioral Intentions

- Motion intention is the anticipation and initiation of movement, stemming from neuromuscular planning and premovement signaling, enabling fluid motor coordination [38, 39].

Psychological cues are measurable indicators that enable cobots to detect and interpret human states in real time, forming the basis for adaptive system responses [40]. This review categorizes these cues into three main types: physiological, behavioral, and neurological measures. This classification aligns with human factors and psychophysiological research frameworks, emphasizing the need for multimodal approaches to assess and respond to human states in dynamic work environments [40].

- *Physiological measures*, such as heart rate variability, blood volume pulse, electrodermal activity, and respiration rate, are recognized as indicators of autonomic nervous system activity and are extensively used to assess stress, fatigue, and cognitive workload [41]. These measures provide objective insights into an individual's psychophysiological state, offering a reliable foundation for real-time adaptation in cobot applications [42].
- *Behavioral measures*, including gaze fixation, eye movements, facial expressions, and task execution timing, capture externally observable indicators of cognitive and emotional states [43]. These measures are crucial for evaluating attentional engagement, mental workload, and motion coordination, enabling cobots to dynamically adjust interaction parameters and optimize task flow and collaboration quality [44, 45].
- *Neurological measures*, such as brain electrical activity, pupil dilation, and functional near-infrared spectroscopy, provide direct insights into cognitive processing, decision-making, and mental effort [46]. These signals offer a more precise assessment of cognitive load compared to physiological and behavioral measures, making them particularly valuable for high-precision adaptive systems [47, 48].

The impact of the cobots' adaptation on HRC was categorized into two main dimensions: performance outcomes and worker well-being. This classification aligns with established research in human factors, adaptive automation, and occupational ergonomics, which highlight the dual importance of optimizing task efficiency while safeguarding human workers' cognitive and emotional states in collaborative robotic environments [30, 49].

- *Performance outcomes* reflect how cobots enhance task execution, encompassing task performance, task efficiency, error reduction, and task completion time. These metrics are widely used in HRC research to assess whether adaptive systems improve productivity, accuracy, and operational effectiveness [50, 51].
- *Workers' well-being* considers the psychological and physiological effects of cobot adaptation on human collaborators, including perceived workload, stress, fatigue, comfort, and trust in the cobot. These factors are essential for evaluating the sustainability and acceptability of human–robot interactions. Prolonged exposure to high workload, stress, or discomfort can negatively impact worker engagement, safety, and long-term job satisfaction [52, 53]. Trust in automation, particularly in collaborative settings, plays a fundamental role in shaping workers' reliance on cobots and their effectiveness in shared tasks [43].

3. Results

3.1. Risk of Bias and Quality of Studies. Table 1 presents the quality assessment and risk of bias for the studies included in this review. Of the 23 studies considered, 13 (56.5%) met high-quality standards, exhibiting low risk of bias across all evaluated criteria, while the remaining 10 studies (43.5%) were assessed as having moderate quality due to methodological limitations. No studies were classified as low quality across all criteria. All studies demonstrated a clear causal structure, and the majority displayed methodological rigor with respect to measurement consistency, statistical appropriateness, participant comparability, and reliability of outcome assessment. However, several design-related limitations were identified: 5 studies did not employ pre–post measurements, reducing the ability to assess temporal change; 4 studies lacked a control group, limiting the internal validity of their findings; and 2 studies reported incomplete follow-up data.

Sample characteristics also varied across the included studies. The 23 studies involved a total of 331 participants (mean age = 28.2 years) with individual study samples ranging from 4 to 45 participants. This diversity in sample sizes reflects the experimental nature of research in this emerging field, where controlled laboratory settings often necessitate smaller, focused participant groups to ensure precise measurement of psychological states and adaptive mechanisms. Although the majority of individual assessments (91.8%) were rated as low risk of bias, some structural limitations and sample size variations may temper the conclusion that the evidence base is uniformly strong. Consequently, while the overall methodological quality was evaluated as high, such limitations should be explicitly considered when interpreting the strength and generalizability of findings on psychological state–based adaptive systems in HRC.

TABLE 1: Quality assessment and risk of bias based on the JBI checklist.

Citation	Variable causality	Participant similarity	Comparable intervention	Control group presence	Pre–post measurement	Follow-up/difference analysis	Measurement consistency	Outcome measurement reliability	Statistics appropriateness
Berg-Yuen et al. [54]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bettoni et al. [55]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Buerkle et al. [56]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Camilleri et al. [57]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Chiurco et al. [58]	✓	?	?	✗	✓	✗	✓	✓	✓
Freire et al. [59]	✓	✓	✓	✗	✗	?	✓	✓	✓
Hostettler et al. [60]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hu et al. [61]	✓	✓	✓	?	✓	✓	✓	✓	✓
Huang et al. [62]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Kirchner et al. [63]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Korivand et al. [64]	✓	✓	✓	✓	✗	✓	✓	✗	✓
Lagomarsino et al. [65]	✓	✓	✓	✓	✓	✗	✓	✓	✓
Landi et al. [66]	✓	✓	✓	?	✓	✓	✓	✓	✓
Lin et al. [67]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ojsteršek et al. [68]	✓	✓	✓	?	✓	✓	✓	✓	✓
Ramachandruni et al. [69]	✓	✓	✓	✓	?	✓	✓	✓	✓
Roveda et al. [70]	✓	✓	✓	✓	✓	✓	✗	✓	✓
Sanna et al. [71]	✓	✓	✓	✗	✗	✓	✓	✓	✓
Singh et al. [72]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Solovey et al. [73]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Yang et al. [74]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Yang et al. [75]	✓	✓	✓	✓	✓	✓	✓	✓	✓
Zhou et al. [76]	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: ✓ = low risk of bias; ✗ = high risk of bias; ? = unclear risk of bias.

3.2. Data Distribution. Figures 2 provides an overview of the data extracted from the studies included in this review, illustrating the distribution of cobot configurations, working sectors, and psychological states and cues.

Most studies focus on single-arm cobots, which are widely used for collaborative tasks in structured environments. Their prevalence in the literature suggests they are the most investigated configuration for adaptive HRC. In contrast, dual-arm and semiautonomous cobots are explored less frequently. They are typically studied in settings requiring more complex manipulation and coordination, while teleoperated robots appear in highly specialized applications where remote control is essential. The lower presence of these configurations in research indicates that their adoption and study may still be limited to specific domains or use cases.

Research on cobots' adaptation mechanisms is largely concentrated in manufacturing, where cobots assist in assembly, pick-and-place operations, disassembly, and quality control. This reflects the well-established role of cobots in structured, repetitive industrial tasks. Other sectors, such as medicine, leverage cobots for surgical assistance and blood suctioning, highlighting their potential in precision-based tasks that require high accuracy and reliability. Logistics applications primarily focus on object transport and sorting. At the same time, space research investigates cobot-assisted task allocation and planetary operations, demonstrating an interest in autonomous robotic support for high-risk and remote missions. By contrast, defense and military applications are only marginally explored, indicating that research on cobots' adaptation in these contexts remains in its early stages. Similarly, catering is addressed in just one study, suggesting that research into cobot adaptation for service-oriented tasks is still highly limited.

Regarding psychological states, the studies included in this review primarily focus on cognitive states, particularly those related to workload, attention, and task engagement. This reflects a strong research emphasis on optimizing cognitive efficiency and supporting mental processing in HRC. Emotional states are also considered, particularly in scenarios where psychological strain, such as stress and fatigue, may affect performance and safety. By contrast, behavioral intentions are examined less frequently, likely due to their specialized application in fields requiring real-time motion prediction and coordination. The predominance of cognitive states in the literature highlights a focus on decision-making support and cognitive workload management in collaborative robotic systems.

Studies predominantly rely on physiological measures to assess psychological states, emphasizing an objective, real-time approach to detecting cognitive and emotional states. Behavioral measures are also commonly used, particularly in studies investigating adaptive cobot interactions that require real-time behavioral monitoring. Additionally, neurological measures provide deeper insights into cognitive processing and engagement, reinforcing a preference for data-driven adaptation strategies over self-reported assessments.

No graphical representation is provided for adaptive mechanisms and impact on HRC, as a visual aggregation of findings would be less meaningful given the context-dependent nature of adaptation strategies. Each adaptation mechanism is designed to respond dynamically to specific psychological states and operational requirements, making it difficult to generalize their effectiveness across different applications.

The findings indicate that adaptation mechanisms based on workers' psychological states tend to positively influence HRC. In most studies (21 out of 23), adaptation contributes to improved task efficiency, enhanced fluency in collaboration, reduced cognitive load, and increased worker acceptance. These results suggest that when adaptive mechanisms effectively align with cognitive and emotional cues, they can enhance task performance and worker well-being.

3.3. Adaptation to Cognitive States. Cobots' adaptation to humans' cognitive states is central to HRC, influencing decision-making, task performance, and workers' well-being across diverse work environments. The findings indicate that cognitive workload, situational awareness, attention, cognitive conflict, and task engagement are the primary cognitive states considered in adaptive cobot systems, with cognitive workload being the most frequently addressed [72, 73].

Cobots typically respond to fluctuations in workload by modulating task complexity, execution speed, and autonomy levels to maintain efficiency and reduce cognitive strain. These adaptations are especially common in manufacturing, logistics, and medicine, where task distribution and execution pacing are adapted in real time to match operators' cognitive demands [60, 67]. In robot-assisted assembly tasks and surgical procedures, workload regulation strategies involve automating repetitive processes or varying the level of robotic assistance based on cognitive strain detection [57].

Beyond workload, situational awareness and attention emerge as critical states in environments requiring continuous monitoring, precision, and responsiveness, like manufacturing, logistics, and defense [67, 71]. In these sectors, cobots enhance HRC by modifying interaction timing, issuing real-time alerts, and adapting visual or haptic feedback to keep operators engaged and responsive. In collaborative manufacturing, cobots dynamically adjust task handovers and intervention thresholds based on fluctuations in operator attention, ensuring fluid coordination between human and robotic agents [71]. Similarly, cognitive adaptation mechanisms in high-risk operations such as military decision-making and space teleoperation help manage workload by modulating automation levels based on operator strain. This reduces cognitive load during high-pressure scenarios while maintaining human oversight when demands decrease [54, 73].

Cognitive conflict arises from competing task demands and decision-making under uncertainty, which is another key cognitive factor addressed in adaptive cobot systems [72, 73]. In logistics and space operations, cobots mitigate cognitive conflict by balancing automation, adapting interface complexity, and reallocating tasks proactively. For example, in robotics-assisted navigation, cobots adjust task delegation and control mechanisms in response to high cognitive load and conflict, ensuring smoother interaction and

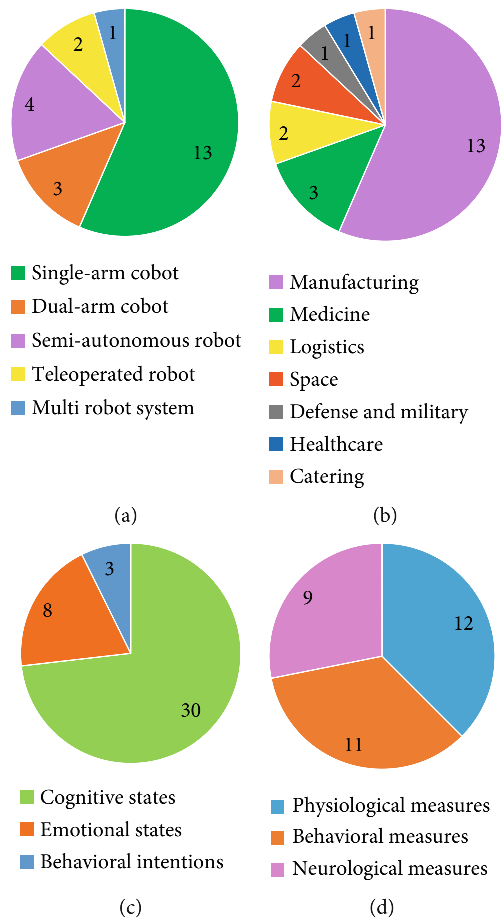

Figure 2: Cobot configurations (a). Working sectors (b). Psychological states (c). Psychological cues (d).

reducing execution errors [72]. The ability to dynamically adapt in these situations is particularly useful in environments where human–robot synchronization is essential for operational safety and efficiency.

Task engagement is also monitored and used to adapt the cobot's behavior, as variations in engagement determine task complexity adjustments and workload distribution. Cobots infer engagement fluctuations and adapt support mechanisms to sustain consistent involvement in the task. In assembly and disassembly tasks, cobots monitor human movement patterns and execution timing to redistribute workload or slow execution to maintain engagement [59, 69]. Similarly, in quality control inspection, cobots adjust execution speed and task allocation based on task engagement levels [61, 64]. In collaborative catering and space operations, cobots adjust handover strategies or message frequency based on detected engagement levels, ensuring fluid task execution and workload balance [62, 63].

Across various settings, cognitive states are assessed through psychophysiological cues, enabling cobots to dynamically respond to human mental demands. Pupil dilation, EEG activity, and heart rate variability are frequently used to infer cognitive workload and conflict, while eye-tracking systems and depth cameras capture situational awareness and attention fluctuations [67, 71–73]. Hence, cognitive adaptations are primarily designed to optimize cognitive efficiency and reduce task-related strain, leading to more effective task execution, better workload management, and improved coordination between human workers and cobots. While manufacturing and logistics prioritize workload regulation and attentional support, medical, military, and space applications increasingly focus on real-time cognitive state monitoring to enhance precision and decision-making under pressure.

3.4. Adaptation to Emotional States. Cobots' adaptation to emotional states contributes to more effective HRC, particularly in work environments where psychological strain impacts performance, safety, and worker well-being. The findings indicate that stress and fatigue are the most frequently addressed emotional states. At the same time, self-confidence and discrete emotions (i.e., happiness, sadness, anger, surprise, fear, and disgust) are less commonly explored but offer emerging insights into human–cobot interaction.

Stress and fatigue are widely considered in adaptive cobot systems, particularly in manufacturing and logistics, where physiological and behavioral indicators allow cobots to detect workers' emotional strain. Cobots regulate task allocation and execution speed to mitigate stress-induced overload and fatigue-related performance decline. For example, during plastic injection molding tasks, cobots dynamically redistribute workload and suggest rest breaks when high stress or fatigue levels are detected via electrodermal activity and heart rate variability [55]. Similarly, in pick-and-place assembly tasks, cobots adjust movement speed and task distribution to accommodate fatigue-related cognitive strain, ensuring smoother operations and reducing execution errors [56]. Stress-responsive adaptations extend to teleoperated manufacturing, where cobots activate guiding forces to assist operators under high emotional strain, improving precision while maintaining efficiency [66]. Self-confidence–based adaptation has also been explored. Cobots infer operator confidence levels through heart rate variability and visual perception in logistics applications. When low self-confidence is detected, cobots increase automation, ensuring task support while allowing greater operator control when confidence improves [67].

Additionally, some cobots incorporate emotion-sensitive adaptation to refine task coordination and interaction fluidity. In sequential handover tasks, cobots analyze workers' facial expressions using deep learning–based recognition to infer emotions like anger, sadness, or frustration. When frustration-related emotions are detected, cobots dynamically adjust their speed or pause interactions to enhance coordination and prevent errors [58]. Despite their potential, emotion-based adaptations remain limited, partly due to real-time facial recognition accuracy challenges and individual variability in emotional expression.

Across various work environments, emotional states are primarily assessed through physiological and behavioral cues, including heart rate variability, electrodermal activity, respiration rate, and facial expression analysis [64, 68]. While stress and fatigue adaptation mechanisms are widely implemented in industrial applications, emotion-based adaptation remains an emerging area of research with potential benefits for refining HRC and enhancing workplace well-being.

3.5. Adaptation to Behavioral Intentions. Cobots' adaptation to behavioral intentions enhances HRC by dynamically adjusting movement-based interactions in response to human motion cues. Among these behaviors, motion intention is the primary factor in adaptive cobot systems. These adaptations enable cobots to interpret human movement cues and fine-tune their physical responses, ensuring smoother task execution and reducing operator strain. Motion intention is integrated into adaptive cobot systems across manufacturing, healthcare, and logistics, where human-applied force, body movement, and motion tracking guide real-time robotic adjustments. In gear insertion tasks, cobots modify impedance by adjusting stiffness and damping levels in response to detected motion intention, ensuring precise collaborative movements [70]. Similarly, in dressing assistance for healthcare, cobots alter their trajectory modifications and real-time force feedback according to human motion intention, resulting in smoother handovers and fewer execution errors [57]. In logistics applications, cobots regulate stiffness settings when handling objects, decreasing stiffness for high motion intention and increasing it when motion intention is lower, optimizing operator support and safety [61]. Cobots rely on motion tracking, applied force sensors, and electromyography to evaluate workers' motion behaviors, enabling real-time mechanical adjustments based on human actions [57, 61]. These findings indicate that motion-aware cobots improve movement coordination, task efficiency, and worker ergonomics in different work environments.

Table 2 provides a comprehensive synthesis of the included studies and the data extracted and charted during the review process.

4. Discussion

This review examined which worker psychological state collaborative robots adapt to during joint human–robot tasks in work environments. The review focused exclusively on experimental studies that tested the effectiveness of these adaptive systems in enhancing HRC. By synthesizing the available evidence, we identified the psychological states most frequently considered in adaptive cobot systems, the mechanisms used for real-time assessment, and their impact on collaboration effectiveness and worker well-being.

This work provides novel insights distinguishing it from previous literature on adaptive collaborative robotics. While existing reviews have primarily focused on task allocation strategies or physical safety considerations [7, 16], our work provides the first systematic synthesis of real-time psychological state-based adaptation in collaborative work environments. Our systematic categorization for psychological states, assessment methods, and adaptation mechanisms bridges psychological science with robotics engineering, advancing research in this interdisciplinary field.

The results highlight that cobots predominantly adapt to workers' cognitive states, particularly cognitive workload, attention, and situational awareness. This strong emphasis on cognition reflects an ongoing research focus on optimizing decision-making efficiency and task execution in HRC. Cognitive workload emerged as the most frequently addressed state, with cobots dynamically modifying task complexity, execution speed, and autonomy levels to regulate workers' mental strain [72, 73, 76]. These adaptation strategies are particularly prevalent in manufacturing, logistics, and healthcare, where cognitive efficiency is a key determinant of performance and safety [65, 68, 74].

Adaptation to emotional states, such as stress and fatigue, was less frequently explored than cognitive states but still recognized as significant. Stress-responsive cobots adjust task allocation and pacing to mitigate cognitive overload [55, 64, 66], whereas fatigue-adaptive systems modify execution speed to sustain worker engagement [56, 60]. However, real-time adaptation to discrete emotions remains underdeveloped, with only a few studies investigating cobots' ability to detect and respond to variations in self-confidence or frustration [58, 67]. This limited focus on emotional adaptation may stem from the complexity of accurately interpreting and responding to emotions in real time and the stronger emphasis on cognitive states, which are more directly linked to task performance and operational efficiency. Moreover, the variability of emotional expressions across individuals and contexts makes it challenging to

TABLE 2: Summary of the included studies and extracted data.

Citation	Robot configuration	Working sector	Collaborative task	Humans' psychological state(s)	Humans' psychological cue(s)	Assessment tool(s)	Adaptive mechanism(s)	Impact on overall HRC
Berg-Yuen et al. [54]	Robotic munition deployed in an aerial vehicle	Defense and military	Military search and strike operation	Cognitive workload	Brain electrical activity Eye movements Heart rate variability	ECG sensor EEG system Eye tracker	Adaptation of task control, increasing automation for high cognitive workload and switching to human decision-making for low cognitive workload	Improved task execution time Reduced workers' cognitive load
Bettoni et al. [55]	Single-arm collaborative robot	Manufacturing	Plastic injection molding	Fatigue Stress	Electrodermal activity Heart rate variability Motion capture data Skin temperature	Chest strap with ECG sensor Motion tracking system Wearable device with sensors for PPG, EDA, and accelerometry	Real-time task reallocation, assigning more assembly steps to the cobot for high stress or fatigue and fewer for low stress or fatigue. Break suggestion, prompting rest periods when fatigue is detected	Enhanced work engagement Improved task execution time Reduced quality issues Reduced workers' mental stress Reduced workers' physical stress
Buerkle et al. [56]	Single-arm collaborative robot	Manufacturing	Pick-and-place assembly of a mechanical component	Cognitive workload Fatigue Stress	Brain electrical activity Heart rate variability Respiration rate	EEG sensor ECG sensor Respiration sensor	Speed adjustment, slowing down for high cognitive workload or fatigue and maintaining standard speed for low cognitive workload, stress or fatigue Real-time adjustment of task distribution, taking over more pick-and-place operations for high cognitive workload, fatigue, or stress and reducing assistance for low cognitive workload, fatigue, or stress	Improved task execution time Reduced performance errors Reduced workers' cognitive load
Camilleri et al. [57]	Dual-arm collaborative robot	Healthcare	Dressing	Attention Cognitive workload Motion intention	Human applied force Motion capture data	Force sensors for interaction measurement Motion tracking suit	Adjustment of dressing trajectory, modifying movements for high motion intention, cognitive workload, or attention shifts. Real-time force feedback adjustment, decreasing force for movement disruptions and increasing force for synchronized movements	Improved task execution time Reduced workers' cognitive load
Chiurco et al. [58]	Single-arm collaborative robot	Manufacturing	Sequential handover in a slab polishing production line	Emotions (happiness, sadness, anger, surprise, fear, disgust, neutrality)	Facial expressions	Facial recognition system using convolutional neural networks	Adjustment of cobot speed, maintaining standard speed for neutral or slightly happy emotions and decreasing speed or pausing for frustration-related emotions such as sadness, anger, or fear	Improved task execution time Noted limitations in facial recognition-based adaptation

TABLE 2: Continued.

Citation	Robot configuration	Working sector	Collaborative task	Humans' psychological state(s)	Humans' psychological cue(s)	Assessment tool(s)	Adaptive mechanism(s)	Impact on overall HRC
Freire et al. [59]	Single-arm collaborative robot	Manufacturing	Disassembly of electronic waste	Cognitive workload Task engagement	Body movement Human motion trajectory Task execution timing	Vision-based recognition system for worker tracking and gesture detection	Task adaptation, assigning more complex disassembly tasks for high task engagement or low cognitive workload and redistributing easier tasks for low task engagement or high cognitive workload. Real-time error management, offering step-by-step guidance or slowing task execution when an error is detected	Reduced performance errors Increased perceived comfort Enhanced perceived safety
Hostettler et al. [60]	Single-arm collaborative robot	Manufacturing	LEGO assembly	Cognitive workload Stress	Pupil dilation Human movement patterns	Depth camera with motion-tracking capability Eye tracker	Adjustment of cobot speed and trajectory, decreasing speed and modifying trajectory for high cognitive workload or stress, and maintaining standard speed and trajectory for low cognitive workload or stress	Increased trust in the cobot Increased perceived comfort
Hu et al. [61]	Dual-arm collaborative robot with integrated force sensors	Logistics	Object transport	Cognitive workload Motion intention Task engagement	Human motion trajectory Surface electromyography	sEMG sensors with software for muscle activity and motion analysis	Adjustment of cobot stiffness, decreasing for high motion intention, task engagement, or cognitive workload and increasing for low motion intention, task engagement, or cognitive workload	Enhanced perceived safety Improved task execution time Reduced workers' cognitive load
Huang et al. [62]	Single-arm collaborative robot	Catering	Dish unloading	Attention Task engagement	Body movement Hand movement distance and time	Depth camera with motion-tracking capability	Adjustment of handover strategy, waiting or slowing down for low attention or task engagement and switching between proactive and reactive handovers for high attention or task engagement	Improved task execution time Increased collaboration fluency Reduced workers' cognitive load
Kirchner et al. [63]	Multirobot collaborative system	Space	Task allocation	Cognitive workload Task engagement	Brain electrical activity	EEG system with 64 electrodes	Adjustment of task allocation and message frequency, reducing task load and spacing out messages for high cognitive workload or task engagement, and increasing task load and message frequency for low cognitive workload or task engagement	Improved task execution time Increased worker engagement Reduced worker cognitive load

TABLE 2: Continued.

Citation	Robot configuration	Working sector	Collaborative task	Humans' psychological state(s)	Humans' psychological cue(s)	Assessment tool(s)	Adaptive mechanism(s)	Impact on overall HRC
Korivand et al. [64]	Single-arm collaborative robot with vision system for part delivery	Manufacturing	Quality control inspection of a manufactured part	Stress Task engagement	Blood volume pulse Electrodermal activity Heart rate variability	Wearable device with sensors for PPG, EDA, accelerometry, and skin temperature	Adjustment of cobot speed, decreasing for high stress or low task engagement and increasing for low stress or high task engagement	Reduced performance errors
Lagomarsino et al. [65]	Single-arm collaborative robot with adaptive gripper	Manufacturing	Assembly of an aluminum component	Cognitive workload Stress	Body movement Gaze fixation Galvanic skin response Head pose Heart rate variability	Depth camera with skeleton tracking ECG sensor EDA sensor	Adjustment of robotic assistance and action transparency, increasing support and clarity for high cognitive workload or stress and reducing them for low cognitive workload or stress	Increased trust in the robot Reduced workers' cognitive load
Landi et al. [66]	Teleoperated dual-arm industrial robot	Manufacturing	Pick-and-place manipulation in teleoperation	Cognitive workload Stress	Heart rate variability	Smartwatch with PPG sensor	Activation of assistive virtual fixtures, enabling guiding forces for high stress or cognitive workload and maintaining standard operation for low stress or cognitive workload	Improved task execution time Reduced workers' stress Reported trade-off between assistance and freedom of motion
Lin et al. [67]	Semiautonomous wheeled mobile robot	Logistics	Ball collection and sorting	Attention Self-confidence Situational awareness	Heart rate variability Pupil response Visual perception	Eye tracker Monitoring camera Wearable device with sensors for PPG, EDA, and accelerometry	Real-time switching between human instruction and autonomous behavior, increasing autonomy for low attention, situational awareness, or confidence and decreasing autonomy for high attention, situational awareness, or confidence	Improved task execution time Optimized decision-making
Ojsteršek et al. [68]	Single-arm collaborative robot	Manufacturing	Assembly of a semifinished product	Cognitive workload Stress	Blood volume pulse Heart rate variability	Portable ECG sensor with heart rate variability analysis software	Adjustment of cobot speed, decreasing for high cognitive workload or stress and increasing for low cognitive workload or stress	Reduced stress Maintained time task execution
Ramachandruni et al. [69]	Single-arm collaborative robot	Manufacturing	Drill assembly	Cognitive workload Task engagement	Human movement patterns Task execution timing	Depth camera with skeletal tracking system for body movement and posture monitoring	Adjustment of task sequencing, prioritizing simpler tasks for high cognitive workload or low task engagement and more complex tasks for low cognitive workload or high task engagement	Increased intention to use the cobot Reduced workers' cognitive load Reduced task execution time

TABLE 2: Continued.

Citation	Robot configuration	Working sector	Collaborative task	Humans' psychological state(s)	Humans' psychological cue(s)	Assessment tool(s)	Adaptive mechanism(s)	Impact on overall HRC
Roveda et al. [70]	Single-arm collaborative robot	Manufacturing	Insertion of a gear into a shaft and application of caulking	Motion intention	Human applied force Motion tracking	Force sensors for interaction measurement	Adjustment of cobot impedance, decreasing stiffness and damping for high motion intention and increasing them for low motion intention	Enhanced perceived collaboration quality Improved task execution time Reduced physical effort
Sanna et al. [71]	Single-arm collaborative robot	Manufacturing	Assembly of a vise, including component selection and pick-and-place	Attention Cognitive workload	Eye movements Visual cortex activity	AR-based attention tracking system EEG sensor	Adjustment of cobot execution, delaying actions and providing visual feedback for low attention. Speed adjustment, slowing down for high cognitive workload. Real-time task guidance, suggesting recalibration and pausing execution when cognitive workload is detected	Enhanced perceived usability Improved task execution time Reduced worker cognitive load
Singh et al. [72]	Single-arm collaborative robot	Manufacturing	Material handling	Cognitive conflict Cognitive workload	Brain electrical activity	EEG system with 32 electrodes	Tuning of interaction forces and control parameters, decreasing for high cognitive workload or conflict, and increasing for low cognitive workload or conflict	Improved task execution fluency Reduced cognitive conflict
Solovey et al. [73]	Semiautonomous planetary mobile rover	Space	Mars rock classification	Cognitive conflict Cognitive workload	Brain activity	Functional near-infrared spectroscopy	Adjustment of communication frequency and autonomy levels, reducing interactions for high cognitive workload or conflict, and increasing engagement for low cognitive workload or conflict	Improved task execution time Reduced worker cognitive load
Yang et al. [74]	Semiautonomous robotic-assisted surgical system with suction tool	Medicine	Needle passing in a surgical procedure	Cognitive workload	Brain electrical activity Fixation duration Scan path length	ECG sensor Eye tracker	Activation of the cobot to pass the needle when a high cognitive workload is detected	Improved task execution time Reduced workers' cognitive load
Yang et al. [75]	Semiautonomous robotic-assisted surgical system with suction tool	Medicine	Blood suctioning in a surgical procedure	Cognitive workload	Brain electrical activity Gaze fixation Pupil dilation	ECG sensor Eye tracker	Activation of the cobot's suction tool, triggered when high cognitive workload is detected	Improved task execution time Reduced workers' cognitive load
Zhou et al. [76]	Teleoperated dual-arm robotic surgical system	Medicine	Minimally invasive surgery for a urological procedure	Cognitive workload	Brain electrical activity Electrodermal activity Heart rate variability	ECG sensor for heart rate variability EDA sensor EEG headset	Dynamic adjustment of visual and haptic feedback, enhancing guidance and stabilizing robotic motion for high cognitive workload, and maintaining standard feedback for low cognitive workload	Reduced workers' cognitive load

design universally effective adaptation strategies, probably contributing to the fewer studies in this area.

Adaptation to behavioral intentions emerged as a method for enabling seamless physical coordination between humans and cobots. Motion intention–driven adaptation is particularly relevant in assembly, healthcare, and logistics, where robots must interpret human movement cues to adjust trajectory, stiffness, or impedance [57, 61, 70]. However, cognitive state adaptation remains the dominant focus, highlighting the need for future research to explore hybrid approaches integrating both cognitive and behavioral intention–based adaptations for more fluid and intuitive HRC.

4.1. Implications and Limitations of the Study. The findings of this review offer insights into the evolving role of adaptive cobots in work environments, particularly in how psychological state–based adaptation is shaping HRC. The emphasis on cognitive states as primary adaptation targets suggests that research in this area is primarily driven by the goal of optimizing cognitive efficiency and task performance. While this focus aligns with established principles in human factors and cognitive ergonomics, it also raises questions about the potential trade-offs between cognitive and emotional adaptation. The relative underrepresentation of emotional states in adaptive mechanisms indicates that affective factors, which play a role in motivation, engagement, and stress regulation, remain less explored in cobot interaction strategies.

At a practical level, the growing reliance on physiological and behavioral cues for adaptation reflects a shift toward more data-driven approaches to HRC. This reliance introduces both opportunities and challenges. On the one hand, real-time assessment of workers' psychological states allows for dynamic workload distribution, potentially reducing cognitive strain and improving efficiency. For engineers and system designers, this highlights the need for robust, multimodal assessment methods that ensure accuracy while minimizing invasiveness, as well as the importance of designing cobots capable of adapting seamlessly to diverse work environments and individual differences. For organizations and industry stakeholders, the integration of adaptive cobots raises considerations regarding workforce training, operational costs, and acceptance. The effectiveness of adaptation strategies may depend on how well they align with existing workflows, team structures, and industry-specific demands.

On the other hand, the use of physiological data for adaptation raises concerns about privacy, data security, and ethical oversight, particularly in workplaces where continuous monitoring could be perceived as intrusive. Policymakers and regulatory bodies play a key role in establishing guidelines that balance innovation with worker rights, ensuring that adaptive technologies are implemented transparently and equitably. The extent to which workers perceive such mechanisms as beneficial rather than intrusive remains an essential factor in their adoption, requiring organizations to consider participatory approaches that involve employees in the design and deployment of adaptive systems. As cobots continue to expand across industries, long-term success will likely depend on striking a balance between technological advancements, ethical considerations, and human-centered design principles.

Another consideration concerns the predominantly unidirectional nature of adaptation mechanisms observed in the reviewed studies. While cobots effectively respond to human psychological states, limited attention is given to how workers adapt to changes in robot behavior. Previous research has demonstrated that transitions between different robot control strategies can significantly affect human movement performance and adaptation processes [77], while automation level choices influence key human experience metrics such as flow, agency, and embodiment [78]. This suggests that effective adaptive systems may benefit from bidirectional adaptation frameworks that account for both robot responsiveness to human states and human responsiveness to robot behavior modifications, enhancing the ecological validity of adaptive cobot systems for real-world implementation.

Despite its novel contributions, this study inevitably has some limitations. First, the focus on in-lab experimental studies may not fully represent real-world settings, where adaptation mechanisms must contend with broader operational constraints. While controlled laboratory environments allow for precise measurement and validation of adaptive cobot behaviors, they may not capture the complexities of industrial workflows, unexpected disruptions, or the influence of social and organizational factors on HRC.

Second, this review does not assess the effectiveness of different adaptation strategies in the long term, as the included studies primarily focus on short-term experimental evaluations. Most studies assess adaptation mechanisms within single-session interactions, limiting the ability to determine how HRC evolves over prolonged periods. This temporal limitation reveals a gap in understanding the distinction between immediate, reactive adaptations and the long-term dynamics that characterize mature collaborative relationships. Extended collaboration may involve different mechanisms, including the development of trust, mutual learning patterns, and workers' behavioral adaptation to robot responses, which could significantly influence the sustainability and effectiveness of psychological state–based adaptation strategies over time.

5. Conclusions

The results of this study lead to some considerations. Firstly, the prominence of cognition as the primary focus in current research on cobot adaptation in work environments deviates from social robotics adaptation research, which primarily emphasizes adaptation to human emotional responses—see, for example, Hong et al. [79] and Tuyen et al., [80]. Social robotics research often prioritizes affective computing and emotion recognition, aiming to develop robots capable of engaging in socially meaningful interactions by responding to users' affective states. In this domain, the objective is to enhance social bonding and user engagement, particularly in contexts such as healthcare and education. In contrast, cobot adaptation in industrial work environments primarily revolves around optimizing cognitive states to improve task performance, decision-making, and operational efficiency.

This emphasis on cognition aligns more closely with research on ergonomic adaptation, which, beyond focusing on physical well-being, recognizes cognitive workload reduction as a key factor in workplace safety and productivity [81, 82]. The convergence of psychological and engineering disciplines in this field indicates a broader shift toward designing adaptive systems that dynamically balance task demands based on real-time assessments of cognitive states. This underscores the potential for interdisciplinary collaboration in refining robot adaptation strategies for workplace implementation, integrating insights from cognitive psychology, human factors engineering, and artificial intelligence to develop more sophisticated models of human–robot interaction.

Secondly, our findings highlight a growing alignment of research objectives with human-centered automation principles, which emphasize the role of technology in augmenting human capabilities rather than replacing them. This echoes one of the main concerns regarding emerging technologies, not only within research but also in broader societal discourse [83]. In this context, the focus on adapting to cognitive states reflects a shift toward automation strategies that actively support human workers by dynamically distributing the workload between humans and robots and adjusting task execution accordingly. This approach is aimed at enhancing both performance and safety by ensuring that cobots function as adaptive partners rather than static tools, optimizing task execution while preventing mental fatigue and cognitive overload.

Finally, our review underscores the increasing reliance on physiological signals to assess workers' mental states, reflecting a trend toward using objective, real-time indicators of cognitive and emotional conditions. While physiological measures offer relevant insights, their use as standalone indicators presents limitations, as they may not fully capture the complexity of mental states or account for individual variability. A multimodal assessment approach, integrating physiological, behavioral, and neurological cues, would provide a more comprehensive understanding of workers' psychological conditions, enabling cobots to adapt more effectively and reliably. Future advancements in adaptive robotics could further refine these methods, enhancing the precision and responsiveness of cobot adaptation mechanisms to support dynamic and cognitively demanding work environments.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics Statement

This study did not involve human participants or animal subjects requiring ethical approval.

Conflicts of Interest

The authors declare no conflicts of interest.

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