Collaborative Synergy in Industry: Exploring Human-Robot Interaction and Cognitive Robotics

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Abstract

In the new era of Industry, characterized by transformative technological shifts, robots have become integral to manufacturing. This paper delves into human–robot interaction (HRI), specifically emphasizing human–robot collaboration (HRC). As robots play pivotal roles in sectors like manufacturing, understanding collaboration dynamics becomes imperative. HRC involves humans and robots jointly pursuing shared objectives, emphasizing the development of cognitive models for enhanced performance. Simultaneously, the field of cognitive robotics aims to create intelligent robots with adaptive behaviors, integrating insights from AI, cognitive science, and robotics. Providing an overview of current trends, challenges, and research directions, this paper explores the intersection of HRI and Cognitive Robotics. Navigating the landscape of collaborative synergy between humans and cognitive robots offers insights into the transformative potential of this dynamic field in the industrial realm.

1. Introduction

The onset of a transformative era in manufacturing, characterized by the integration of cyber-physical systems, the Internet of Things (IoT), and networked communication, marks a significant shift in the industry's landscape (Schwab, 2016). This revolution signifies a comprehensive reevaluation of traditional approaches in production, management, and governance, propelling industries toward an era where digital interconnectivity and intelligent automation become the new standard (M. Xu et al., 2018).

Within this context, the role of intelligent robotic technologies, or Robotics 4.0 emerges as critical in revolutionizing the industrial operational framework. Through the integration of advanced sensory technologies and sophisticated learning algorithms, intelligent robotic systems possess the capability to dynamically recalibrate their actions, tool configurations, or programming in alignment with changes in product specifications or production exigencies (Cao et al., 2020). This adaptability is a cornerstone in the evolution of flexible manufacturing systems that are proficient in accommodating a diverse range of tasks and product types (Soori et al., 2024). Advancing from the substantial progress made by Robotics 3.0, which introduced as deep learning, digital twinning, and human-robot natural interaction, Robotics 4.0 is set to further revolutionize the field with the introduction of the Internet of Robots, Brain-on-Cloud (BoC) technology, the Artificial Intelligence of Things (AIoT), the deployment of 5G networks and deep learning and integrations of robot cognitive skills (Gao et al., 2020).These advancements enhance system capabilities through deep learning and cognitive skills for more sophisticated and connected solutions (Hwang

& Tani, 2018). A greater autonomy and decision-making in robots represent a crucial advancement, integrating them more seamlessly into industrial and everyday settings.

Within this technological landscape, the domains of Human-Robot Interaction (HRI) and Human-Robot Collaboration (HRC) stand as essential components, marking a transition towards more integrated and interactive manufacturing environments. HRI is concerned with crafting systems that facilitate effective understanding and communication between humans and robots (Sheridan, 2016), while HRC delves into collaborative scenarios where humans and robots share tasks and environments (Krüger et al., 2009). This collaborative dynamic not only boosts productivity and safety but also drives innovation by creating manufacturing systems that are both adaptable and resilient (Wang et al., 2017).Therefore, the progression of HRI and HRC is key to fulfilling the vision of the new landscape of industry, merging human-centric operations with robot-assisted processes to innovate manufacturing and service sectors.

In 2021, the EU witnessed a 5.5% rise in non-fatal work accidents and a marginal decrease in fatal accidents, signaling a need for enhanced occupational safety despite technological advancements in sectors like manufacturing, which experienced 19.2% of these non-fatal incidents (Statistics Explained, 2023). The persistence of work-related musculoskeletal disorders, among an aging workforce and evolving work environments, further accentuates this need (Crawford et al., 2020). The European Commission recognizes the necessity of supporting worker protection standards, considering the substantial yet insufficient 70% decrease in accidents since 1994 (European Commission, 2021).With new technologies introducing complex challenges, the reevaluation of health and safety protocols, particularly concerning AI and robotics, becomes crucial to mitigate emerging risks and ensure a safer, more resilient workforce in the face of industrial transformation (European Commission, 2019).

In the nexus of these technological breakthroughs, Cognitive Robotics (CR) emerges as an area of particular intrigue. It seeks to provide robotic systems with a level of adaptive intelligence that parallels human cognitive functions, thereby facilitating more sophisticated and anticipatory interactions with their environment (Vernon, 2014). The realization of this adaptive intelligence is facilitated through the application of bio-inspired methods, which inform the design of sensorimotor, cognitive, and social capabilities in autonomous robots (Cangelosi & Asada, 2022). The integration of CR with HRC leads in the era of Cognitive HRC, a burgeoning field that is assured to revolutionize the collaborative dynamics between humans and robots. (Han et al., 2021). Emphasizing Cognitive HRC underscores a transition towards robots that are not only context-aware and decision-capable but also intuitive and responsive to human nuances (Fischer & Demiris, 2019; Moulin-Frier et al., 2018; Nakamura et al., 2018; Tan & Huan, 2011). Therefore, the pursuit of CR and Cognitive HRC is critical, promising to harness the transformative power of Industry 4.0 and drive us toward a future where collaborative intelligence is intrinsic to both industrial efficiency and societal advancement.

2. Cognitive Robotics

2.1. Definitions

CR represents a concerted endeavor to construct intelligent systems that embody physical form, drawing heavily on methodologies from cognitive and natural sciences (Stein, 1997). De Giacomo

(1998) situated CR at the confluence of reasoning, perception, and action, stressing the necessity of a unified theoretical and practical framework. This field is not merely about the automation of tasks but about equipping robots with the ability to navigate dynamic and partially unknown environments through sophisticated knowledge representation and reasoning (Levesque & Lakemeyer, 2008). Further emphasizing the need for robots to exhibit human-like intelligence, Kawamura and Browne (2009) pointed to the integration of advanced perception, motor control, and cognitive functions as key aspects of CR. In essence, CR synthesizes insights from artificial intelligence (AI) with cognitive and biological sciences to foster the development of robots that can think, learn, and interact in ways that emulate human beings. As Cangelosi and Asada (2022) articulated, CR integrates these diverse strands of knowledge to enhance the autonomous capabilities of robots, propelling them beyond mere machines to entities capable of intelligent behavior and social interaction.

The discipline encompasses a wide array of applications, from cognitive modeling with both simulated agents and physical robots to software agents and hardware-based smart objects (Morris, 2005; Vernon, 2014). It also includes the design of intelligent human-computer interaction systems, known as cognitive systems engineering (Woods & Roth, 1988), and extends to general-purpose AI systems like IBM Watson (High, 2012). A significant contribution of cognitive systems research is the provision of an operational definition of cognition that captures its full complexity. Vernon (2014) offered a comprehensive delineation of cognition within artificial systems, portraying it as an integrative process through which an autonomous entity perceives its environment, learns from experiences, anticipates potential outcomes, takes goal-directed actions, and adapts to evolving contexts. Cognition, hence, is conceptualized as a systemic attribute, weaving together the core functionalities of an agent—autonomy, perception, learning, anticipation, action, and adaptation (Figure 1).

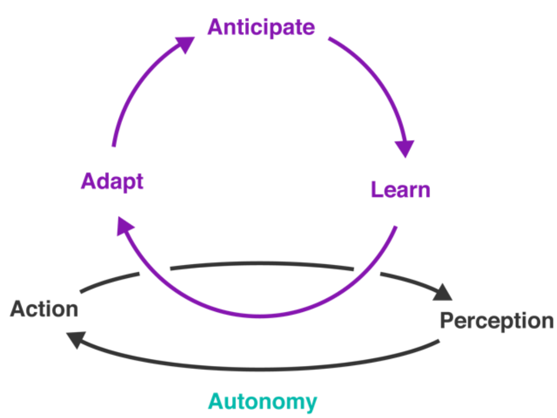

Figure 1: The six key attributes of cognition in artificial cognitive systems. Source: Adapted from Vernon 2014.

2.2. Cognitive Architectures

A cognitive architecture serves as the foundational software framework for systems designed to emulate the capabilities of a cognitive agent. It delineates the structure and organization of a cognitive system, encompassing the constituent parts or modules that facilitate cognitive processing (Sun, 2004).

Within the Cognitivist (Symbolic) Perspective, cognitive architectures are centered on the invariant aspects of cognition—those that remain stable over time and across different tasks(Langley et al., 2009; Ritter & Young, 2001). This perspective posits that cognitive functions can be represented by symbols and rules that are manipulated within the architecture, akin to software running on a computer.Conversely, the Emergent (Embodied) Perspective posits that cognition arises through the developmental processes of an agent as it interacts with its environment (Vernon, 2022). This approach emphasizes the necessity of an environment beneficial to development, balancing regularity for understanding and variability for stimulating growth without overwhelming the agent's developmental pace. Emergent cognition is thus characterized by two core elements—phylogeny, which is the architecture itself, and ontogeny, the accumulation of experiences as the agent's cognitive capabilities advance. The most adopted approach in contemporary research is the Hybrid Architecture. These architectures amalgamate elements from both symbolic and emergent paradigms to capitalize on their respective strengths. (Kotseruba & Tsotsos, 2020) note a significant prevalence of hybrid architectures, with their survey identifying 22 symbolic, 14 emergent, and 48 hybrid systems, 38 of which exhibit full integration.

Despite the challenges in establishing a universally accepted definition of cognition and the complexities of delineating intelligence, scholars concur on the existence of core cognitive abilities that underpin cognitive processes. These foundational capabilities include perception, attention, action selection, memory, learning, reasoning, metacognition, and prospection (Kotseruba & Tsotsos, 2020; Vernon, 2014). In addition to the core cognitive abilities that underpin the functioning of cognitive systems, there is a recognized consensus on the pivotal role of social cognition abilities for fostering effective interactions and collaborations between humans and robots (Yukie Nagai, 2022). Social cognition encompasses the capabilities essential for recognizing and managing oneself in relation to others, as well as for applying and interpreting social signals during interactions. These capabilities include Self-Other Recognition, enabling robots to distinguish between themselves and human partners; Joint Attention, which allows robots and humans to focus on the same object or task cooperatively; Reading Intentions, the ability of robots to understand and predict human actions and intentions; and Altruistic Behavior, where robots can exhibit actions that benefit their human counterparts.

CR merges diverse disciplines to forge systems with nuanced intelligence and autonomy. Core and social cognitive abilities are crucial for deepening the symbiosis between humans and robots, pushing the boundaries of collaboration and innovation in this dynamic field.

3. Human-Robot Collaboration HRC in Industry

Human-Robot Interaction (HRI) encompasses the multifaceted interplay and communication exchanges that occur when humans and robots engage in a common task, facilitated by an interface that encompasses all system aspects and procedures designed for user interaction (ISO 8373:2012, ISO 11064-5:2008).

HRI has been meticulously categorized from various analytical standpoints. Initiated by Yanco and Drury (2004), the taxonomy encompasses criteria such as task nature and criticality, robot morphology, human-to-robot ratios, team composition, interaction levels, proximity, decision-making support, temporality, spatial arrangement, and autonomy. Schmidtler et al. (2015)further refined this understanding by identifying four key dimensions—workspace sharing, timing of work, goal alignment, and the presence of physical contact—thus delineating the spectrum of human-robot relations from coexistence through cooperation to collaboration. Building on this conceptual framework, subsequent studies Wang et al. (2017) introduced additional considerations such as the spatial-temporal relationship between agents, the multiplicity of agents, and leader-follower dynamics. These contributions enriched the taxonomy by articulating the complex interplay of autonomy and collaborative roles within industrial applications.

Building upon these foundations, additional dimensions such as shared workspace, direct contact, shared task work, simultaneous and sequential processes were brought to the forefront (Prati et al., 2021; Vincent Wang et al., 2018). These aspects underscore the gradations of intimacy in human-robot relations, from independent yet simultaneous operation to a synchronized dance of collaborative efforts. The classifications suggest a matrix where human-robot pairs may engage in varying degrees of overlap in their tasks, with implications for safety and efficiency.

To attain a comprehensive perspective, it is crucial to consider the entire contextual framework in which human-robot interactions occur (Apraiz et al., 2023). This holistic approach encompasses, on one hand, human characteristics—ranging from socio-demographic profiles, motivational drives, self-perceptions, prior experiences, and knowledge to the influence of subjective social norms, behavioral intentions, and the individual's position within the team structure. On the other hand, it involves task characteristics, including the imperative of safety, the intricacies of task design, the implications of the technology employed, the reliability of the processes, the degree of flexibility afforded, and the autonomy and control available to operators. Finally, the characteristics of the context and organization are integral, covering the spectrum from the nature of relationships between operators and executives, to the dynamics with immediate supervisors, the availability and clarity of information, the scope for participatory decision-making, the quality of relationships between colleagues, the provision of support, the ergonomics and design of the workplace, the intensity of work demands, the management of changes within work systems, the adequacy of remuneration, and the sufficiency of support and training provided.

In the continuum of HRI taxonomy, recent systematic reviews have illuminated practical guidelines. The emerging guidelines underscore the importance of trust, a factor that interfaces significantly with the established dimension of decision-making support and autonomy (Simões et al., 2022). The attribution of blame, technology acceptance, and human cognitive performance are intricately linked with the nature and criticality of tasks, shaping the proximal and temporal coordination between humans and robots. Furthermore, the guidelines suggest that comfort and safety are not peripheral but central to the taxonomy's considerations of proximity and shared task work. Moreover, the integration of continuous self-learning mechanisms within robotic agents is identified as a critical frontier for advancing HRI. Such developments would not only refine the robots' cognition modeling but also foster a personalized interaction experience for the collaborating human workforce (Jahanmahin et al., 2022). This emergent research advocates for robots that are context-aware, transcending static programming to actively learn and adapt to the nuances of human behavior, including emotional cognition and decision-making processes.

The field of HRI extends beyond mere operational taxonomies to a profound comprehension of the intricacies inherent in collaborative endeavors. Central to this evolution is the pivotal role of trust, the flexibility of role dynamics, and the importance of a shared cognitive framework. These approaches underscore the necessity of a synergistic affinity between human ingenuity and robotic efficiency. It is imperative that future developments in collaborative robotics not only focus on the refinement of functional interactions but also foster enhancements in joint cognitive capabilities, thereby engendering an enriched collaborative landscape that leverages the unique strengths of both human and robotic agents.

4. Intersectionality between Human-Robot Collaboration and Cognitive Robotics

As the frontier of intelligent automation expands, the interdisciplinary nexus of CR and HRC emerges as a critical area of study. The rapid proliferation of literature in these areas needs a methodical examination of conceptual trends to chart the current landscape and anticipate future directions. This section utilizes the bibliometric capabilities of VosViewer, an analytical tool adept at distilling complex data into intelligible maps of thematic concentrations (Van Eck et al., 2010), to analyze key trends and delineate the convergence points of these two pivotal fields. Through this analysis, we aim to articulate a scholarly narrative that encapsulates the intellectual fusion of CR and HRC, offering a foresight into their collaborative potential.

4.1. Methodology

A search string comprising the following terms was used to query the Lens.org database: "Human" AND "Robot" AND "Collaboration" (Human AND (Robot AND Collaboration)) for the first search and "Human" AND "Robot" AND "Collaboration" AND "Cognitive" AND "Robotics" (Human AND (Robot AND (Collaboration AND (and AND (Cognitive AND Robotics))))) The search string in Lens.org was based on the database titles, abstracts and keywords.

To delineate the interconnectivity and thematic evolution within the domains of CR and HRC, a bibliometric network analysis was conducted utilizing VOS Viewer. This involved the creation of two distinct lexical maps: the first one exclusively focused on HRC and the second one charting the research terrain of CR in concert with HRC. These maps were constructed by evaluating 'keyword co-occurrence' within the dataset derived from academic publications, with 'co-occurrence' signifying the frequency of adjacent appearances of keywords. In the generated lexical network, terms are positioned within a two-dimensional space predicated on their co-occurrence rates and associative strength with other keywords. The proximity between two terms in this space signifies the likelihood of their conceptual relatedness—the closer two terms are, the stronger their theoretical association (Van Eck et al., 2010). Each term's label and circle size are indicative of its prominence, determined by the number of its connections and the total intensity of these connections (Van Eck & Waltman, 2017). Clusters of terms represent groups of closely interconnected terms, as delineated by the weighted and parameterized modularity function. To ensure a focused analysis, a threshold for inclusion was set, considering only those keywords with a minimum of 10 co-occurrences (Van Eck & Waltman, 2017). Additionally, a Thesaurus was assembled in Excel to amalgamate synonymous concepts, such as 'HRI' and 'Human-Robot Interaction,' for analytical consistency.

4.2. Lexical Networks

4.2.1. Human Robot Collaboration

The final corpus consisted of 7117 articles, the keyword co-occurrence analysis found 72 terms that meet the threshold (number of co-occurrences of a keyword >40). The Lexical Networks map in Figure 2., indicates a research landscape where "robot", "human robot collaboration", and "human" are central, suggesting a focus on integrating robots into human-centric environments and systems. The importance of "system" and "environment" denotes a holistic approach to robotic integration, while "control" and "motion" highlight the dynamics of interaction. The presence of "learning" and "AI" reflects an emphasis on adaptable, learning-capable robots. Key themes include technological advancement, with an overarching human-centered design approach underscored by terms like "user" and "operator", pointing to a field driven by human needs and technological innovation. Further cluster analysis highlights 5 distinct thematic domains within the research landscape, each color-coded cluster reflecting cohesive areas of inquiry:

- Green Cluster: Collaboration and flexibility in robotic integration within production and workspaces.
- Yellow Cluster: User-centered research on the interaction and perception between humans and robots.
- Red Cluster: Technical focus on robot control, motion, and task simulation.
- Blue Cluster: Cognitive and learning capabilities of robots, including prediction and intention understanding.
- Purple Cluster: System-wide integration of robots, emphasizing AI and environmental interaction.

The proximity of terms like "system", "environment", "control", "motion", and "learning" to the central nodes implies these are also significant topics, heavily connected to the core subjects. The layout seems relatively balanced with no overly isolated clusters, implying a cohesive field where different subtopics maintain relevance to each other. The spread of nodes indicates a diversity of research within the field, covering technical, cognitive, and systemic aspects of HRC.

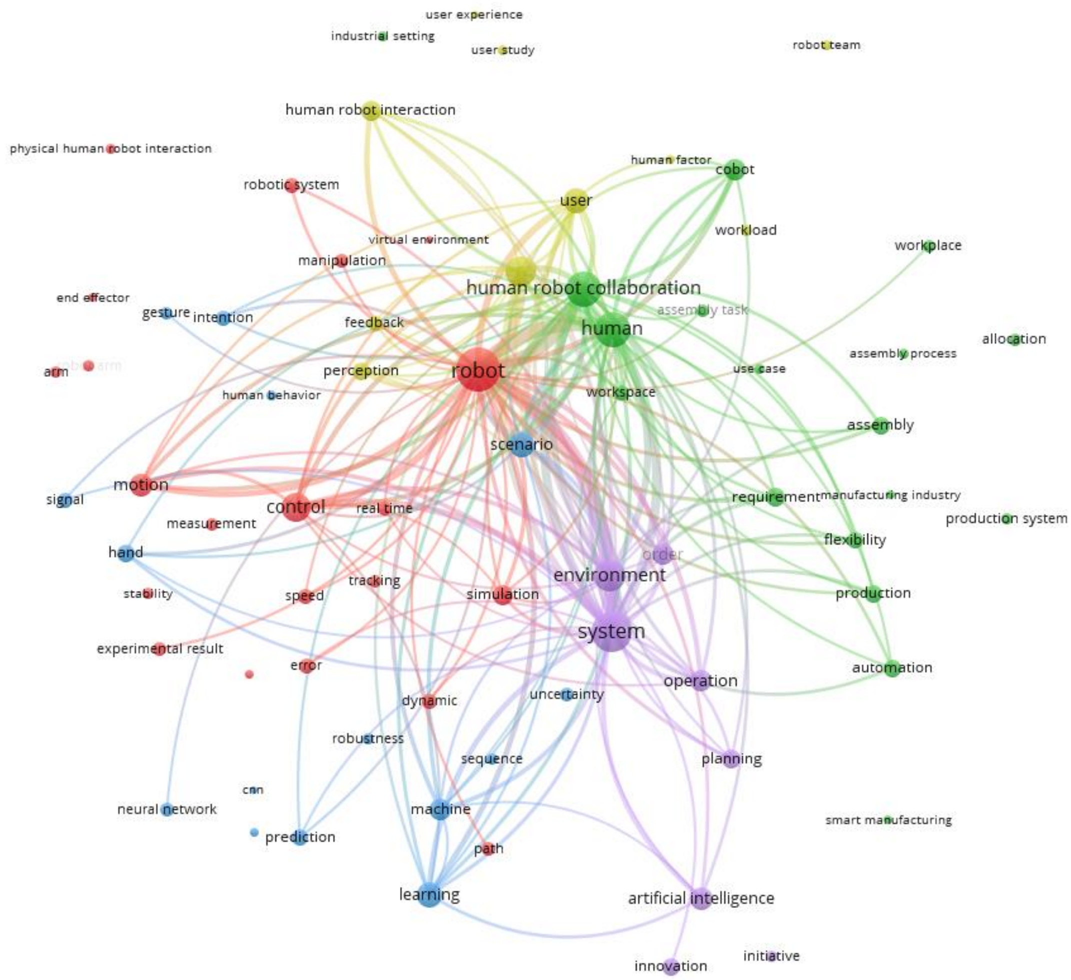

Figure 2: Vos Viewer Lexical network, Human-Robot Collaboration

4.2.2. Human Robot Collaboration and Cognitive Robotics

The final corpus consisted of 1719 articles, the keyword co-occurrence analysis found 78 terms that meet the threshold (number of co-occurrences of a keyword >15). The Lexical Networks map in Figure 3 shows the terms "Human Robot Collaboration," "Human," "Collaboration," "Robot," "Performance," "Capability," "Behavior," "Challenge," "Framework," and "Trust" which stand out as the conceptual pillars of the map. These terms represent the fundamental aspects of the research landscape, spanning from the theoretical basis to practical applications and the inherent challenges of the field. Further cluster analysis highlights 4 distinct thematic domains within the research landscape, each color-coded cluster reflecting cohesive areas of inquiry:

- Blue Cluster: Interaction between humans and robots, emphasizing the roles and performances of both operators and cobots in collaborative tasks.
- Yellow Cluster: Intrinsic attributes of robots and their interactions with humans, underpinned by concepts of capability, behavior, theoretical foundations, and trust.

- Green Cluster: Challenges in HRC, discussing the frameworks and integration strategies, as well as the decision-making processes and communication methods required for effective reasoning and collaboration.
- Red Cluster: Cognitive and computational backbone of the field.

The lack of a dominant central node linking the clusters indicates a field with distinct, specialized research areas in HRC and CR. This suggests a landscape where sub-disciplines are emerging with their own focused research agendas rather than a single, cohesive narrative. The connections between these clusters are notably weak, highlighting a research community where interdisciplinary engagement is still maturing. Compared to the previous map's robust interconnectivity, this map suggests a discipline in a state of development, with potential for greater cross-disciplinary integration as these subfields evolve. This network's configuration underscores the dynamic nature of the field, reflecting an academic landscape that prioritizes depth in specialized areas while gradually forging inter-domain linkages.

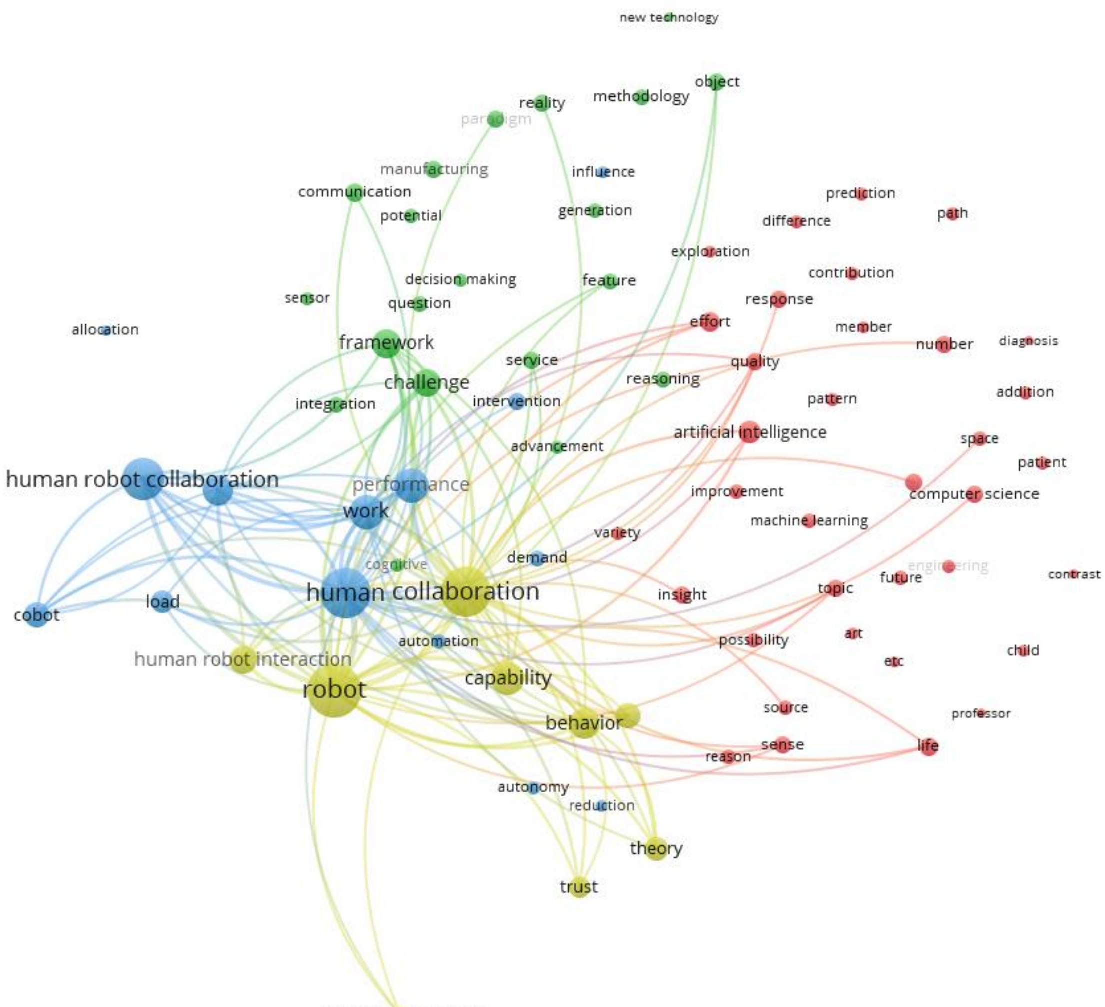

Figure 3: Vos Viewer Lexical network, Human-Robot Collaboration and Cognitive Robotics

5. Challenges and Opportunities for Future research directions

Integrating the VOSviewer lexical analysis, we can discern that the current research terrain within HRC and CR is both fragmented and ripe for further exploration. The VOSviewer analysis revealed a landscape where key cognitive and collaborative themes in robotics are burgeoning, yet not cohesively integrated, signaling a clear directive for future research to bridge these domains more effectively. To navigate this complex terrain and propel towards a more interdisciplinary research nexus between HRC and CR, three primary areas have been identified: the contributions of CR to HRC, the influence of HRC in the evolution of CR, and the interplay of cognitive systems and ethical considerations. Addressing these themes will not only consolidate the existing research but also catalyze the development of an integrated field where the symbiosis of HRC and CR can thrive, underpinned by a robust ethical framework. This discussion sets forth to unravel these areas, guiding a path forward for an enriched, interdisciplinary research trajectory.

5.1. Cognitive Robotics contributions in Human-Robot Collaboration

In the context of HRC, a major challenge is the navigation of unforeseeable environmental dynamics(Zsolt Kemény et al., 2021), which is reflected in the lexical network analysis where 'Uncertainty,' 'Environment,' and 'System' are interlinked. These interdependencies within the research underscore the complexity of developing adaptable and resilient HRC systems. The technological progressions in CR hold promise for integration into HRC, by enhancing control, motion, and safety within collaborative operations. The field of Neurorobotics, for example, is making advances by merging neural mechanisms with robotic systems to produce robots capable of more complex and human-like behavior (Hwu & Krichmar, 2022). Innovations such as the muscle-signal-reading wristband from CTRL-Labs, now a project of Meta Platforms(Melcer et al., 2018), exemplify breakthroughs in robot controllability and communication. Additionally, Soft Robotics introduces a new approach with robots made from flexible materials that can navigate and adapt to their surroundings more effectively than traditional robots. This adaptability is critical when working alongside humans, particularly in handling intricate tasks(Hughes et al., 2022). Companies like Soft Robotics Inc. have demonstrated the practical benefits of such technology with their robotic grippers that can manage sensitive tasks across different industries, showcasing the adaptability of CR to real-world variability (Terrile et al., 2021).

The maps also indicate a proliferation of Machine Learning (ML) applications in HRC, yet reveal an underrepresentation of in-depth HRC models, aligning with the findings of Natarajan et al. (2023). The integration of ML in HRC is paving the way for robots that not only learn from and adapt to human behavior but also anticipate and make decisions that enhance collaboration. Within Cognitive Robotics (CR), diverse methodologies elucidate the integration of learning and decision-making in robots. This progression mirrors the evolution from basic collaborative robots to those capable of complex cognitive functions, as seen in Developmental Robotics, Evolutionary Robotics, and Swarm Robotics. Each of these branches of Cognitive Robotics represents a leap towards replicating or understanding human-like cognition and interaction within robots, signifying a confluence of goals between HRC models and Cognitive Robotics advancements. Developmental Robotics, for instance, draws from developmental psychology, attempting to replicate the cognitive evolution observed in human infancy. It advances robot design by creating systems like the iCub humanoid robot, which emulates child-like learning through sensorimotor and social engagement, thereby enhancing our grasp of both robotics and cognitive development (Cangelosi & Schlesinger, 2018; Vernon et al., 2007). Evolutionary Robotics applies evolutionary algorithms to refine robotic behaviors, allowing for the natural selection-like optimization of their interactions with dynamic environments (Respall & Nolfi, 2020). Meanwhile, Swarm Robotics, inspired by the complex coordination seen in nature, focuses on the collective behavior of robot groups. This domain benefits from the robust, flexible, and scalable nature of distributed control systems, exemplified by Amazon Robotics' automated warehouse solutions (Girija et al., 2021; Hamann, 2018).

This disparity between the technical advances in CR and the practical application within HRC systems denotes a vital area for academic inquiry and development. As the field matures, fostering a closer integration of these technologies will be essential for realizing the full potential of human-robot partnerships.

5.2. Human-Robot Collaboration contributions in Cognitive Robotics

In the domain of CR, the challenge remains to imbue robots with a semblance of human cognition, a formidable task that encompasses the development of systems that can think, learn, and even experience. Tawiah (2022) highlights the breadth of this challenge, from the recognition of facial expressions and gestures to the implementation of decision-making processes that align with human reasoning. The necessity for rigorous research into Cognitive HRC models is paramount (Inkulu et al., 2022; Natarajan et al., 2023), to inquiry beyond mere functional collaboration and delve into the realm of cognitive empathy and understanding.

The integration of HRC into the development of CR underscores a crucial methodological shift. In particular, for robots with embodied and hybrid cognitive architectures, the interaction with humans is not merely a supplementary feature but a core facet of their cognitive development. Such interactions are paramount to the robots' ontogeny— the progressive accumulation of experiences that shape their learning and maturation processes (Vernon, 2022). In these architectures, engagement with human counterparts and dynamic environments enables robots to evolve beyond preprogrammed responses. Through exposure to human behavior and feedback, these systems learn to interpret complex social cues and adapt accordingly, leading to an enhancement of their cognitive capabilities. Crucial studies supporting this include research by Sethumadhavan (2012), who delves into the anthropomorphic qualities required for believable HRI, Lemaignan et al. (2017) who explore the cognitive skills necessary for shared space and collaborative tasks, and Tsarouchi, Makris, & Chryssolouris (2016) who highlight the challenges of task planning and safety in manufacturing environments, emphasizing the necessity for robots to be able to adapt to and learn from their interactions with humans. The findings from these studies point to a future where the development of cognitive abilities in robots is inextricably linked to their ability to interact with and learn from humans in a collaborative setting.

Within the dynamic interplay of CR development and HRC, a vast research frontier emerges: understanding the implications of robotic cognitive abilities on human users, which is reflected in the lexical network analysis where 'Capability,' 'Automation,' and 'Collaboration' are interlinked and closely allocated. As robots acquire functionalities such as memory, learning, decision-making, and anticipation, it becomes imperative to scrutinize their impact on human interactions. This inquiry extends beyond the technical feat of emulating human cognitive skills in robots; it delves into identifying which cognitive capabilities best enhance HRC. Adopting a user-centered design perspective, we can strategically direct the development of CR towards cognitive functions that not only mimic human intelligence but also enrich the collaborative experience. For instance, how does a robot's ability to remember personal preferences or anticipate human actions influence the user's trust and ease of interaction? What impact does a robot's learning curve have on the user's perception of the robot as a competent and reliable partner? This line of inquiry aligns with the broader goal of enhancing HRC by ensuring that the cognitive evolution of robots is attuned to the nuances of human cognition and social dynamics. A deep dive into this facet of CR could yield insightful guidelines for designing robots that are not just capable but also socially compatible with their human collaborators.

Thus, while robots advance in mimicking cognitive processes, the cultivation of social cognitive abilities seem to be paramount for enhancing their ability to engage meaningfully in HRI. Social cognitive abilities such as Self-Other recognition, Joint attention, and Reading intentions are critical for developing robots that can understand and predict human behavior. These abilities enable the creation of an internal model of the interacting agent, which is foundational to metacognition. Such an internal model, rooted in the theory of mind, allows the attribution of mental states—intentions, beliefs, desires—to others, which is essential for seamless interaction (Curioni et al., 2017). Aligned with these principles, Decision and Control Action Scheme (DCAS) framework represents an HRC model that embodies metacognition, facilitating dynamic role adaptation between human and robot agents for cooperative decision-making (Curioni et al., 2017). The framework embodies principles of cooperative decision-making and dynamic action, wherein both human and autonomous agents can interchangeably assume lead and co-lead roles contingent on task exigencies. Effective communication and cooperation between the agents are deemed imperative for accomplishing shared objectives while ensuring safety and efficiency. Alongside, the Proactive HRC paradigm pushes the boundaries further, leveraging these capabilities for anticipatory collaboration (Li et al., 2021). This innovative model is predicated on a triad of advanced cognitive teamwork competencies: (i) inter-collaboration cognition, which fosters a shared understanding and empathy between humans and robots; (ii) spatio-temporal cooperation prediction, enabling the anticipation of interactive dynamics over the continuum of collaborative tasks; and (iii) self-organizing teamwork, which cultivates collective intelligence within the manufacturing ecosystem. Together, these models highlight the promise of social cognitive abilities in enhancing robot-human interactions, signaling a rich direction for research into cognitively inspired HRC systems.

5.3. Cognitive systems and ethics

Although absent from the lexical networks displayed in the VosViewer map, the dimension of ethics constitutes an indispensable consideration within the domains of Human-Robot Collaboration (HRC) and Cognitive Robotics. The imperative to interrogate and integrate ethical principles is paramount, as it shapes the trajectory of societal integration and responsible innovation in these rapidly evolving fields.The profound advancements in machine learning and cognitive computing elevate the ethical stakes, as these technologies equip robots with decision-making capabilities once solely attributed to humans. Addressing ethical concerns is not merely about instilling robots with a set of pre-determined moral codes but also about ensuring they operate within frameworks that respect human rights, privacy, and dignity. Incorporating inclusive design is vital as well for creating systems that are truly beneficial for a diverse range of users, to ensure that robotic systems are accessible and usable by people with varying abilities, backgrounds, and experiences. Future research must, therefore, extend beyond technical and cognitive proficiency to encompass the creation of ethical guidelines that govern robot behavior, particularly in scenarios of close HRI. This entails considering issues such as informed consent in human-robot data sharing, bias in decision-making algorithms, and the broader societal impacts of deploying autonomous robotic systems.

As an example of a potential future research direction, Wei Xu Zaifeng Gao's insights into human-AI teaming (HAT) present a paradigmatic shift in human-AI systems, emphasizing the importance of a human-centered AI (HCAI) approach (2023). This framework illustrates a future research trajectory that embraces the synergy of human cognition, robotic technology, and ethical consideration. The HAIJCS framework does not view humans, technology, and ethics as separate entities but as interconnected facets that must be considered holistically to achieve harmonious and effective human-AI teaming. This model stands at the forefront of HRC research, seeking to establish a human-centered AI (HCAI) paradigm where AI is more than a tool—it is a collaborative partner capable of augmenting human abilities and contributing to joint performance.

6. Conclusions

This paper has examined the emergent synergy between CR and HRC, revealing their pivotal role in shaping the future of industrial automation. Our bibliometric analysis via VOSviewer has illuminated key trends and convergence points between CR and HRC. It presents an academic narrative ripe for further exploration, advocating for a more interconnected research paradigm. Key findings indicate that while advancements in CR have led to more autonomous and adaptable robotic systems, integrating these advancements effectively within HRC practices remains a challenge. The implications of these technologies extend beyond increased productivity; they offer the potential for safer work environments and the decrease of monotonous tasks for human workers.

As we move forward in the field of collaborative intelligence, we must also address the ethical ramifications of these technologies. Future research must balance technical innovation with ethical foresight, ensuring that as robots become more cognitively adept, they do so in a manner that respects human values and augments human capabilities. To address these multifaceted challenges, cross-disciplinary research is imperative. Future work should therefore draw on the expertise of various fields such as engineering, computer science, psychology, ethics, and design, to develop robust HRC models that are ethically grounded and practically viable. Additionally, research should be directed towards addressing the gap between technological capability and its real-world applicability, ensuring that the benefits of CR and HRC are fully realized in practical settings. By acknowledging these limitations and focusing on these recommendations, the field can progress towards a more cohesive and responsible integration of CR in human-centric industrial environments.

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8. Bibliography

Apraiz, A., Lasa, G., Montagna, F., Blandino, G., Triviño-Tonato, E., & Dacal-Nieto, A. (2023). An Experimental Protocol for Human Stress Investigation in Manufacturing Contexts: Its Application in the NO-STRESS Project. *Systems*, *11*(9). https://doi.org/10.3390/systems11090448

Browne, W., Kawamura, K., Krichmar, J., Harwin, W., & Wagatsuma, H. (2009). Cognitive robotics: New insights into robot and human intelligence by reverse engineering brain functions [From the Guest Editors]. In *IEEE Robotics and Automation Magazine* (Vol. 16, Issue 3, pp. 17–18). https://doi.org/10.1109/MRA.2009.933617

Cangelosi, A., & Asada, M. (2022). *Cognitive robotics*.

Cangelosi, A., & Schlesinger, M. (2018). From Babies to Robots: The Contribution of Developmental Robotics to Developmental Psychology. *Child Development Perspectives*, *12*(3), 183–188. https://doi.org/10.1111/CDEP.12282

Cao, Z., Zhou, P., Li, R., Huang, S., & Wu, D. (2020). Multiagent Deep Reinforcement Learning for Joint Multichannel Access and Task Offloading of Mobile-Edge Computing in Industry 4.0. *IEEE Internet of Things Journal*, *7*(7), 6201–6213. https://doi.org/10.1109/JIOT.2020.2968951

Crawford, J. O., Graveling, R., Davis, A., Giagloglou, E., Fernandes, M., Markowska, A., & Jones, M. (2020). *Work-related musculoskeletal disorders: from research to practice. What can be learnt? European Risk Observatory Report European Agency for Safety and Health at Work*. https://doi.org/10.2802/118327

Curioni, A., Sebanz, N., & Knoblich, G. (2017). Accepted Manuscript Can we identify others' intentions from seeing their movements? Comment on "Seeing mental states: An experimental strategy for measuring the observability of other minds" by Cristina Becchio et al. *Physics of Life Reviews*. https://doi.org/10.1016/j.plrev.2017.11.018

De Giacomo, G., & Rosati, R. (1998). *Reasoning about High-Level Robot Behaviors by Model Checking and Local Validity Tests*. www.aaai.org

European Commission. (2019). *Revision of the Machinery Directive*. http://ec.europa.eu/growth/sectors/mechanical-engineering/machinery/

European Commission. (2021). *EU strategic framework on health and safety at work 2021-2027 Occupational safety and health in a changing world of work*. https://ec.europa.eu/info/strategy/priorities-2019-2024/economy-works-people/jobs-growth-and-

Fischer, T., & Demiris, Y. (2019). *IEEE TRANSACTIONS ON COGNITIVE AND DEVELOPMENTAL SYSTEMS 1 Computational Modelling of Embodied Visual Perspective-taking*.

Gao, Z., Wanyama, T., Singh, I., Gadhrri, A., & Schmidt, R. (2020). From industry 4.0 to robotics 4.0 - A conceptual framework for collaborative and intelligent robotic systems. *Procedia Manufacturing*, *46*, 591–599. https://doi.org/10.1016/j.promfg.2020.03.085

Girija, P., Mareena, J., Fenny, J., Swapna, K., Kaewkhiaolueang, K., & John Fenny Jin Swapna Kandula Ketsaraporn Kaewkhiaolueang, M. (2021). *Amazon Robotic Service (ARS) Amazon Robotic Service (ARS) WAREHOUS ROBOT-AS-A-SERVICE Amazon Robotic Service(ARS)*. https://pdxscholar.library.pdx.edu/etm_studentprojects

Hamann, H. (2018). Introduction to Swarm Robotics. *Swarm Robotics: A Formal Approach*, 1–32. https://doi.org/10.1007/978-3-319-74528-2_1

Han, L., Yang, S., & Tyroller, Q. (2021). Cognitive human-robot-collaboration in assembly: A framework for cognitive interaction planning and subject study. *Procedia Manufacturing*, *55*(C), 24–31. https://doi.org/10.1016/j.promfg.2021.10.005

High, R. (2012). *Front cover The Era of Cognitive Systems: An Inside Look at IBM Watson and How it Works*.

Hughes, J., Lida, F., & Birrell, S. A. (2022). Field robotics for harvesting: A review of field robotics approaches for harvesting. *Digital Agritechnology: Robotics and Systems for Agriculture and Livestock Production*, 69–94. https://doi.org/10.1016/B978-0-12-817634-4.00009-4

Hwang, J., & Tani, J. (2018). Seamless integration and coordination of cognitive skills in humanoid robots: A deep learning approach. *IEEE Transactions on Cognitive and Developmental Systems*, *10*(2), 345–358. https://doi.org/10.1109/TCDS.2017.2714170

Hwu, T. J., & Krichmar, J. L. (2022). *Neurorobotics : connecting the brain, body, and environment*. 233. https://books.google.com/books/about/Neurorobotics.html?id=fytfEAAAQBAJ

Inkulu, A. K., Bahubalendruni, M. V. A. R., Dara, A., & SankaranarayanaSamy, K. (2022). Challenges and opportunities in human robot collaboration context of Industry 4.0 - a state of the art review. In *Industrial Robot* (Vol. 49, Issue 2, pp. 226–239). Emerald Group Holdings Ltd. https://doi.org/10.1108/IR-04-2021-0077

Jahanmahin, R., Masoud, S., Rickli, J., & Djuric, A. (2022). Human-robot interactions in manufacturing: A survey of human behavior modeling. In *Robotics and Computer-Integrated Manufacturing* (Vol. 78). Elsevier Ltd. https://doi.org/10.1016/j.rcim.2022.102404

Kotseruba, I., & Tsotsos, J. K. (2020). 40 years of cognitive architectures: core cognitive abilities and practical applications. *Artificial Intelligence Review*, *53*(1), 17–94. https://doi.org/10.1007/s10462-018-9646-y

Krüger, J., Lien, T. K., & Verl, A. (2009). Cooperation of human and machines in assembly lines. *CIRP Annals - Manufacturing Technology*, *58*(2), 628–646. https://doi.org/10.1016/j.cirp.2009.09.009

Langley, P., Laird, J. E., & Rogers, S. (2009). Cognitive architectures: Research issues and challenges. *Cognitive Systems Research*, *10*(2), 141–160. https://doi.org/10.1016/j.cogsys.2006.07.004

Lemaignan, S., Warnier, M., Sisbot, E. A., Clodic, A., & Alami, R. (2017). Artificial cognition for social human–robot interaction: An implementation. *Artificial Intelligence*, *247*, 45–69. https://doi.org/10.1016/j.artint.2016.07.002

Levesque, H., & Lakemeyer, G. (2008). Chapter 23 Cognitive Robotics. In *Foundations of Artificial Intelligence* (Vol. 3, pp. 869–886). https://doi.org/10.1016/S1574-6526(07)03023-4

Melcer, E. F., Astolfi, M. T., Remaley, M., Berenzweig, A., & Giurgica-Tiron, T. (2018). CTRL-labs: Hand activity estimation and real-time control from neuromuscular signals. *Conference on Human Factors in Computing Systems - Proceedings*, *2018-April*. https://doi.org/10.1145/3170427.3186520

Morris, B. (2005). Robotic Surgery: Applications, Limitations, and Impact on Surgical Education. *Medscape General Medicine*, *7*(3), 72. /pmc/articles/PMC1681689/

Moulin-Frier, C., Fischer, T., Petit, M., Pointeau, G., Puigbo, J. Y., Pattacini, U., Low, S. C., Camilleri, D., Nguyen, P., Hoffmann, M., Chang, H. J., Zambelli, M., Mealier, A. L., Damianou, A., Metta, G., Prescott, T. J., Demiris, Y., Dominey, P. F., & Verschure, P. F. M. J. (2018). DAC-h3: A Proactive Robot Cognitive Architecture to Acquire and Express Knowledge about the World and the Self. *IEEE Transactions on Cognitive and Developmental Systems*, *10*(4), 1005–1022. https://doi.org/10.1109/TCDS.2017.2754143

Nakamura, T., Nagai, T., & Taniguchi, T. (2018). SERKET: An architecture for connecting stochastic models to realize a large-scale cognitive model. *Frontiers in Neurorobotics*, *12*. https://doi.org/10.3389/fnbot.2018.00025

Natarajan, M., Seraj, E., Altundas, B., Paleja, R., Ye, S., Chen, L., Jensen, R., Chang, K. C., & Gombolay, M. (2023). Human-Robot Teaming: Grand Challenges. *Current Robotics Reports*, *4*(3), 81–100. https://doi.org/10.1007/s43154-023-00103-1

Prati, E., Peruzzini, M., Pellicciari, M., & Raffaeli, R. (2021). How to include User eXperience in the design of Human-Robot Interaction. *Robotics and Computer-Integrated Manufacturing*, *68*. https://doi.org/10.1016/j.rcim.2020.102072

Respall, V. M., & Nolfi, S. (2020). Development of Multiple Behaviors in Evolving Robots. *Robotics 2021, Vol. 10, Page 1*, *10*(1), 1. https://doi.org/10.3390/ROBOTICS10010001

Ritter, F. E., & Young, R. M. (2001). Embodied models as simulated users: Introduction to this special issue on using cognitive models to improve interface design. *International Journal of Human Computer Studies*, *55*(1), 1–14. https://doi.org/10.1006/ijhc.2001.0471

Schmidtler, J., Knott, V., Hölzel, C., & Bengler, K. (2015). Human Centered Assistance Applications for the working environment of the future. *Occupational Ergonomics*, *12*(3), 83–95. https://doi.org/10.3233/OER-150226

Schwab, K. (2016). Introduction of The Fourth Industrial Revolution. *The Fourth Industrial Revolution*, 1–192. https://books.google.com/books?id=ST_FDAAAQBAJ

Sethumadhavan, A. (2012). Human-robot interaction. In *Ergonomics in Design* (Vol. 20, Issue 3, pp. 27–28). https://doi.org/10.1177/1064804612449796

Sheridan, T. B. (2016). *Human-Robot Interaction: Status and challenges*.

Simões, A. C., Pinto, A., Santos, J., Pinheiro, S., & Romero, D. (2022). Designing human-robot collaboration (HRC) workspaces in industrial settings: A systemic literature review. *Journal of Manufacturing Systems*, *62*, 28–43. https://doi.org/10.1016/j.jmsy.2021.11.007

Soori, M., Dastres, R., Arezoo, B., & Karimi Ghaleh Jough, F. (2024). Intelligent robotic systems in Industry 4.0: A review. *Journal of Advanced Manufacturing Science and Technology*, *0*(0), 2024007–0. https://doi.org/10.51393/j.jamst.2024007

Statistics Explained. (2023). *Accidents at work statistics Statistics Explained*. https://ec.europa.eu/eurostat/statisticsexplained/

Stein, L. A. (1997). Postmodular systems: Architectural principles for cognitive robotics. *Cybernetics and Systems*, *28*(6), 471–487. https://doi.org/10.1080/019697297126001

Sun, R. (2004). Desiderata for cognitive architectures. In *Philosophical Psychology* (Vol. 17, Issue 3, pp. 341–373). https://doi.org/10.1080/0951508042000286721

Tan, & Huan. (2011). *A Conceptual Cognitive Architecture for Robots to Learn Behaviors from Demonstrations in Robotic Aid Area*. https://doi.org/10.0/Linux-x86_64

Tawiah, T. (2022). *Machine Learning and Cognitive Robotics: Opportunities and Challenges*. www.intechopen.com

Terrile, S., Barrientos, A., & Terrile, C. S. (2021). *SOFT ROBOTICS: APPLICATIONS, DESIGN AND CONTROL DICIEMBRE 2021*.

Tsarouchi, P., Makris, S., & Chryssolouris, G. (2016). Human–robot interaction review and challenges on task planning and programming. *International Journal of Computer Integrated Manufacturing*, *29*(8), 916–931. https://doi.org/10.1080/0951192X.2015.1130251

van Eck, N. J., & Waltman, L. (2017). Citation-based clustering of publications using CitNetExplorer and VOSviewer. *Scientometrics*, *111*(2), 1053–1070. https://doi.org/10.1007/S11192-017-2300-7/TABLES/4

Van Eck, N. J., Waltman, L., Dekker, R., & Van Den Berg, J. (2010). A comparison of two techniques for bibliometric mapping: Multidimensional scaling and VOS. *Journal of the American Society for Information Science and Technology*, *61*(12), 2405–2416. https://doi.org/10.1002/ASI.21421

Vernon, D. (2014). *Artificial Cognitive Systems A Primer*.

Vernon, D. (2022). *Cognitive Architectures*.

Vernon, D., Metta, G., & Sandini, G. (2007). The iCub cognitive architecture: Interactive development in a humanoid robot. *2007 IEEE 6th International Conference on Development and Learning, ICDL*, 122–127. https://doi.org/10.1109/DEVLRN.2007.4354038

Vincent Wang, X., Wang, L., & Seira, A. (2018). *Classification, Personalised Safety Framework and Strategy for Human-Robot Collaboration* (Issue 1). https://www.researchgate.net/publication/329935915

Wang, X. V., Kemény, Z., Váncza, J., & Wang, L. (2017). Human–robot collaborative assembly in cyber-physical production: Classification framework and implementation. *CIRP Annals - Manufacturing Technology*, *66*(1), 5–8. https://doi.org/10.1016/j.cirp.2017.04.101

Woods, D. D., & Roth, E. M. (1988). Cognitive Systems Engineering. *Handbook of Human-Computer Interaction*, 3–43. https://doi.org/10.1016/B978-0-444-70536-5.50006-3

Xu, M., David, J. M., & Kim, S. H. (2018). The Fourth Industrial Revolution: Opportunities and Challenges. *International Journal of Financial Research*, *9*(2). https://doi.org/10.5430/ijfr.v9n2p90

Xu, W., & Gao, Z. (2023). *Applying human-centered AI in developing effective human-AI teaming: A perspective from human-AI joint cognitive systems*. https://www.researchgate.net/publication/372246925

Yanco, H. A. (2004). *Classifying Human-Robot Interaction: An Updated Taxonomy**.

Yukie Nagai. (2022). Social Cognition. In *Cognitive Robotics*. The MIT Press. https://doi.org/10.7551/mitpress/13780.001.0001

Zsolt Kemény, József Váneza, Lihui Wang, & Xi Vincent Wang. (2021). Human-Robot Collaboration in Manufacturing: A Multi-agent View. In *Adcanced Human-Robot Collaboration in Manufacturing*.

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