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IFAC PapersOnLine 59-10 (2025) 2646–2651

The Embodied Cognition paradigm: a novel approach to advancing Human-Robot Collaboration research

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Abstract: Recent developments in Human-Robot Interaction (HRI) have moved beyond reactive, pre-programmed robot responses, aiming instead for collaborative systems where robots actively anticipate and adapt to human actions. By integrating Artificial Intelligence (AI), robots can now interpret a range of human signals, enhancing the naturalness of interactions and making communication in industrial environments more intuitive. This evolution has expanded research to consider the cognitive aspects of robots. In industrial contexts, Human-Robot Collaboration (HRC) in shared physical workspaces has been extensively studied from the perspective of the human operator. However, there is a notable lack of research on the mutual cognition in interaction between humans and robots, who can act as a whole, intelligent system. This paper aims to explore the ontological foundations first and, then, the epistemological knowledge regarding the emerging patterns of evolved forms of HRC in industrial contexts involving physically shared workspaces. Starting from the concept of embodied cognition, the authors introduce and define the Human-Robot Embodiment (HRE) paradigm. HRE descriptors allow for evaluating, both in the design and operations, the degree of mutual embodiment. Also, the HRE approach benefits are discussed in terms of workplace safety and ergonomics, task performance, and reliability.

Keywords: human factors; collaborative robotics; cognitive robotics; bidirectional learning

1. INTRODUCTION

Traditional HRI involved programming robots to assist humans through deterministic responses to predefined cues. In such systems, robots are limited by a reactive design, following human commands or inputs. As collaborative robotics has been evolving, there is growing interest in creating robots that do more than react passively (Panagou, et al., 2024). These new systems aim at actively - and intelligently - anticipating human actions and engaging with human partners in real-time, adapting to dynamic, collaborative tasks in industrial settings. For example, Su *et al.* (2023) show how multimodal HRI enables robots to simultaneously interpret various signals from the human - including audio, visual, haptic, and emotional signals from humans - thereby providing multi-channel feedback that makes interactions more natural and "human-like". This ability of robots unlocks a dual benefit. First, it allows human partners to intuitively understand the robot's status and feedback, a crucial feature in high-stress or noisy environments, where mental fatigue and cognitive load significantly affect task performance (Panagou, et al., 2023). Meanwhile, it enables the robot to interpret complex instructions and respond effectively to human inputs and needs. The enhancement of HRC is both evident and essential, moving collaboration - intended as interactive cooperation to perform shared tasks efficiently and safely in a common workspace (Ajoudani, et al., 2018) - towards a higher form of mutual integration in task execution. This impacts not only short-term outcomes like task efficiency and product quality (Alessio, et al., 2022), but also long-term working factors, such as safety in the interaction among distinct systems (Nakhal, et al., 2023), ergonomics (Gualtieri, et al., 2020), reliability, and interaction quality (Coronado, et al., 2022)for both humans and robots. The integration of AI into collaborative robots is revolutionizing communication and interaction (Obaigbena, et al., 2024), also reshaping humans' and robots' individual capabilities (Emmanouilidis, et al., 2021), following advanced machine learning algorithms (Leoni, et al., 2024) (Presciuttini, et al., 2024). The intelligence - whether natural or artificial - of the two agents leads to broaden the study and discussion of their collaboration from the purely physical and spatio-temporal dimension to the cognitive domain. The cognitive aspects of the human in HRI have been widely explored, while the robot's adaptive learning mechanisms and its cognitive perception of the human partner and the workspace remain less examined, and even less so their mutual cognitive involvment during interaction. Supporting this, in their comprehensive literature review on HRC, Castro *et al.* (2021) remarked that handover procedures should be smooth and bidirectional to enable fully developed functions, which calls for improved learning mechanisms fostering mutual understanding and coordination. Also, Schneiders *et al.* (2024) advanced the concept of movement synchronization to the one of entrainment, involving cognitive features such as acoustic feedback. Thus, research on HRC is moving towards the epistemology of evolved forms of collaboration, exploring novel concepts such as bidirectional dynamic cognition in interaction, memory learning, bodily involvment, entrainment. About social robots, Groechel *et al.* (2021) discussed the possibility to personalize interaction by an "embodied learning", providing significant implications for the purpose of this study, aimed at exploring advanced levels of HRC within shared industrial workspaces. The embodied cognition paradigm, referred to by Groechel *et al*, originates from

10.1016/j.ifacol.2025.09.445

neurosciences (Chrisley & Ziemke, 2000). An attempt to transfer the embodiment concept within HRC has been done by Wainer *et al.* (2006), however, no existing research fully addresses embodiment from both physical and cognitive perspectives in a bidirectional framework. Accordingly, discussing the HRE as an evolved dimension of is the main scope of this research. This paper is organized as follows. Section 2 represents the core of the study. First, the general scientific interest towards the embodiment concept is explored. Then, its interpretation and use within the main research areas is reported. Finally, relevant embodiment descriptors are extracted in order to prepare for the paradigm shift towards the industrial field. In section 3, the conceptual transfer of the embodiment paradigm is defined through the definition of some HRE descriptors. Finally, in section 4, the strengths, challenges, and future perspectives of the introduced HRE concept are discussed.

2. THE MULTIDISCIPLINARY EMBODIMENT

Consistently with the assumptions made above, we have conducted a search in the Scopus database (accessed in November 2024) using the terms "*embodiment*" OR "*embodied cognition*", in order to explore the research interest across various fields of study. The search yielded nearly 40,000 results, demonstrating an exponential increase in scientific interest since the early 2000s (Figure 1).

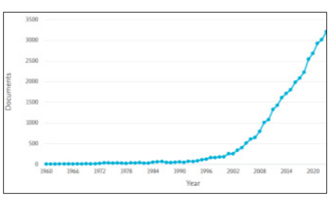

Figure 1. – Documents by year

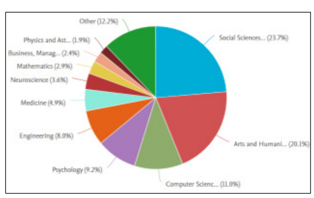

Figure 2. – Doc. by subject

Additionally, the wide range of research fields involving the embodiment paradigm highlights its potential to interpret subtle dynamics in individual behaviors. The research fields identified through the Scopus analysis (Figure 2) can be grouped into clusters. For example, cognitive sciences include philosophy, AI, neuroscience, anthropology, psychology and linguistics (Gartner & Clowes, 2023). Table 1 summarizes the interest share on embodiment concept. Cognitive sciences, together with arts and humanities, and engineering and computer sciences collectively account for nearly 80% of the total scientific research. Cognitive sciences are the primary area, providing foundational concepts and definitions. Arts and humanities category, as the second most explored area, involve the field of performative music. This significant for our study, since musicians search for deep integration with their instruments to accomplish the task, *i.e.*, music performance (Leman, et al., 2017). Although the embodiment concept is rarely referenced in the field of industrial engineering, some studies have investigated the extent of partners' mutual integration, across symbiotic towards proactive HRC (Li, et al., 2023). Thus, knowledge transfer from cognitive sciences, through the domain of performative music, leads to identifying HRE features in industrial applications. Figure 3 summarizes the logical development of this study.

Table 1. Research documents share in embodiment field

Embodiment research area		**Research share**	
Cognitive Sciences	Social Sciences	23,7%	**36,5%**
	Neuroscience	3,6%	
	Psychology	9,2%	
Arts and Humanities			**20,1%**
Engineering and Computer Sciences	Engineering	8,0%	**19,0%**
	Computer Sciences	11,0%	
Medicine			**4,9%**
Math and Physics	Mathematics	2,9%	**4,8%**
	Physics and astronomy	1,9%	
Business, management and accounting			**2,4%**
Other			**12,3%**

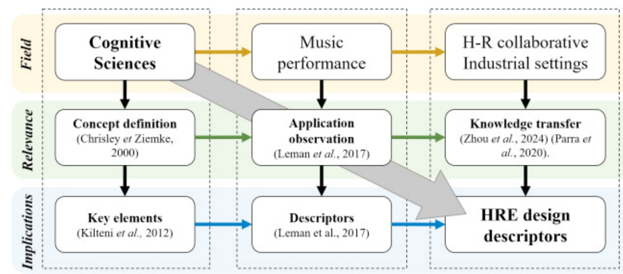

Figure 1. – Study approach

2.1 Cognitive Sciences

The concept of embodiment is rooted in cognitive sciences (Garbarini & Adenzato, 2004), where it refers to the idea that intelligent systems are deeply intertwined with their physical environment and the actions they perform within it. Chrisley *et* Ziemke (2000) classified embodiment across four dimensions: *(i) physical realization*; *(ii) physical embodiment*; *(iii) organismoid embodiment*; *(iv) organismal embodiment.* Kilteni *et al.* (2012) identified three components: body ownership, agency and self-location. Body ownership is the sensation that an external object, is experienced as a part of one's own body. Agency is meant as the sense of control over one's actions and their outcomes. Self-location concerns the experience of where one perceives own body in space. A practical application of this approach can be seen in the study by Segil *et al.* (2022), providing a comprehensive framework for measuring human embodiment across such dimensions examining how patients integrate prosthetic devices.

2.2 Performative music

The observation of contexts in which humans physically interact with a "device" to perform a task is relevant. The field of performative music shows that the integration of musicians with their instruments is essential to the resulting task outcome, revealing how the level of embodiment between human "operator" and "external tool" can influence performance. Such human-tool relationship has driven the research toward the embodied music cognition (Leman, 2007). The work of Leman *et al.* (2017) is the main reference in this section, as it has significant implications for our research. Their approach starts from distinguishing the perception-based cognition from the interaction-based cognition in musical applications. In the perception-based model, musical cognition was primarily connected to memory, learning and prediction. In contrast, interaction-based cognition incorporates body movements and physical experience, providing a richer understanding of music performance as a set of patterns and states. Patterns are the observable elements, while states are the underlying conditions that lead to those patterns. Predictive models in the human brain are adept at inferring these conditions based on observed patterns. However, a relevant uncertainty comes from the brain's internal states (*e.g.*, intentionality, arousal, energy levels), that influence the way the predictive models are constructed: the brain does not directly perceive the external world, but rather constructs models of it through proprioceptive and exteroceptive bodily interactions. Therefore, music performance is understood as a reconstructed experience shaped by the embodied cognition paradigm, observed as an interaction-based cognition where music perception results from an interaction between the perceiver's internal states and the external musical environment. The coupled states of human-environment system generate observable patterns that can help developing predictive models for the human-environment interaction dynamics. Relevant implications are about action anticipation and the expression. Based on the cognitive theory of music, anticipation is generally developed through prior exposure to musical patterns. Prediction operates as a pattern-processing mechanism that functions separately from its physical medium (*e.g.*, the brain). The key elements shaping this cognitive process are: working memory, long-term memory, schema development and automation. These collectively form the cognitive architecture. Furthermore, facial and body expressions play a fundamental role in communication, as they convey emotions and provide insight into affective states (Kret, et al., 2013) (Wei, et al., 2024). Leman (2007) explains that, in music field, expression and expressiveness are closely tied to gestures. The way we perceive music as expressive comes from natural connections between sound and our bodily sensations – *e.g.*, touch, sight, movement, heartbeat - leading to emotional and mood-based associations. As sound moves and changes, human brains naturally link it to physical gestures through a kind of kinesthetic process. Hence, expressive gestures aren't just random movements: they tap into instinctive motor responses that work together with our brain's ability to predict and shape expressiveness. In music, gestures help both in creating expression during performance and in interpreting it, allowing musicians to communicate their artistic intentions more effectively. Decoding occurs during listening, where gestures that support interpretation, as known as "expression-responding" gestures, help listeners interpret the expressive qualities of the music. Seger *et al.* (2014) highlighted the importance of ancillary gestures in musicians, proposing a method to detect them. These gestures, though not directly involved in sound production, are significant in shaping musical expression and the quality of the final performance. While Seger *et al.* do not explicitly reference the concept of embodiment, it is clear that ancillary gestures serve as a meaningful indicator of the depth and quality of the interaction between the musicians and their instruments, reflecting an embodied connection that enhances the expressive impact of the performance.

2.3 Industry

In industrial environments, various terms are used to describe the HR interaction, often reflecting a human-dominant framework, such as human-in-the-loop systems (Bhattacharya, et al., 2023), human-centered work systems (Kadir & Broberg, 2021) and zero-thinking systems (Chiriatti, et al., 2024). Li *et al.* (2023) remark that advanced levels of interaction are essential for tackling complex manufacturing tasks. They propose the proactive HRC as the most advanced collaboration, highlighting key aspects such as shared cognition and empathy, predictable space-time coordination, self-organizing teamwork between humans and robots, adaptive robotic control and anticipatory robotic movements. This approach is representative of current research, focused on augmenting both robot and human perception (Ajoudani, et al., 2018). After all, we remark that both the perception and interaction-based cognition discussed in section 2 are key drivers for task performance, that should be evaluated across the two primary dimensions: the spatial and temporal (Zhou, et al., 2024), and the cognitive one (Parra, et al., 2020). An example is that both human and robot can perceive – in multisensory inputs - the other as an extension of their own body, or rather as an obstacle in the shared workspace.

The embodiment paradigm offers a unifying framework to incorporate such advanced HRC features. For instance, a measure of embodiment can express the bodily involvement during a task, *i.e.*, how seamlessly a physical robot integrates as an extension of the human body or mind, and vice-versa, enabling intuitive and spontaneous interactions. This is exemplified by wearable robots, such as exoskeletons (Xia, et al., 2024). As robots evolve into intelligent, autonomous agents (Licardo, et al., 2024), HRC has expanded to explore how robots can adapt their behavior and perceptions to the human partner during interactions, and vice-versa. Here, the concept of mutual cognition and perception in interaction becomes central, involving new parameters to describe collaboration, such as memory learning, role enactment, entrainment, active participation, anticipation, awareness. While embodiment in other fields is often viewed as a unidirectional concept - where a device is merely operated by a human – it is evident that industrial HRC necessitates a bidirectional perspective, within a new approach moving towards the idea that human and robot form a single entity/system. The study by Wainer *et al.* (2006) first explored the concept of embodiment in HRI with a focus on the robot's perspective. However, it was limited to the physical dimension of the interaction. To understand the HRC evolution steps, we expanded the pathway proposed by Li *et al.* (2023) - focusing on mutual perception and cognitive aspects - by integrating further features deduced from the literature (see Figure 4) moving symbiotic HRC to proactive through four main drivers revealing the degree of mutual integration: *(1)* Sensorimotor coupling SMC, *(2)* Spatial CoLocation SCL, *(3)* Temporal Coordination TC and *(4)* Situation awareness SA.

2.3.1 Sensorimotor Coupling (SMC)

SMC refers to the real-time coordination of sensory inputs and motor actions between the human and the robot. SMC can be quantified through three parameters. *(1) Synchronization*, expressing the similarity between the movements of humans and robots. Motion capture tools can be used to observe the real-time alignment, speed and trajectories of both parties. References can be found in Chua *et al.* (2010), Ge *et* Li (2012), Iqbal *et al.* (2016) and Erden *et* Tomiyama (2010). *(2)Response Delay*, representing the delay between human commands or gestures and the robot's actions. According to the studies of Yamakawa *et al.* (2021) and Duarte *et al.* (2024), it can be measured by machine vision capturing movements' speed. *(3)Force Feedback*, *i.e.* the correlation between human-applied force and the robot's compensatory response in cooperative manipulation (Dawson, et al., 2022). It is measured using force sensors in impedance control schemes (Hogan, 1985), which enabled the system to dynamically adjust the robot's stiffness and damping properties to ensure smooth interaction and maintain stability during tasks.

2.3.2 Spatial Co-Location (SCL)

SCL represents how physically integrated the partners are within the workspace. This has relevant implications in safety and ergonomics design. SCL can be quantified through two factors: *(1)Proximity Index*, indicating the mean reciprocal distance during task execution, measurable through a method based on the integration of LiDAR and depth cameras (Wang, et al., 2025); *(2)Workspace Overlap*, measuring the extent to which human and robot operate within the same space, also quantifying how their movements are coordinated. This is quantified by occupancy grids (Emmanouilidis, et al., 2023).

2.3.3 Temporal Coordination (TC)

TC refers to the synchronization of human and robot actions over time. A higher level of TC increases the likelihood that their tasks remain harmonized, minimizing interference and ensuring smoother collaboration. Relevant factors to measure TC are: *(1)Task Synchronization*, *i.e.,* the alignment of task phases between human and robot, calculated as the cross-correlation of the task over the cycle time. The main difference between task synchronization and movement synchronization is that in the latter are used vectors representing the movements, while for the former here the metrics time-based (*e.g.*: task timely progress, task duration, etc.). *(2)Reaction Time*, indicating the robot's speed in adapting to changes in the human's behavior or unexpected task demands. Higher values of reaction times represent better performance. While the response delay refers to a fixed time lag between operator's command and robot's reaction, reaction time measures how quickly the robot responds autonomously to unexpected human behaviors. This indicates the robot's intuitiveness and spontaneity in accomplishing the assigned task.

2.3.4 Situation Awareness (SA)

SA in robotics refers to the real-time perception of objects and agents within a shared environment, the understanding of ongoing interactions, and the ability to anticipate future developments (Munir, et al., 2022). SA is essential for enabling robots to predict shifts in human actions and task needs. By monitoring human signals and environmental factors, robots are able to adjust in real-time, facilitating an adaptive, proactive approach. From the human side, a very similar perspective of SA comes from the study of Smith *et* Hancock (1995), as well as from Endsley (2023). The extent of SA can be quantified by two main drivers. *(1)Perceptual Accuracy*, assessing how the each agent is able to identify and monitor the partner. From robot's side, it can be measured through object detection, task-state and progress recognition, anomaly detection, using LIDAR, cameras and machine learning algorithms. *(2)Predictive Capabilities*, or the ability to project future states of the interaction with the partner. From robot's side, it is measurable through trajectory prediction, task estimation at complete, human action anticipation basing on neural networks algorithms and time-series analysis.

3. CONTRIBUTIONS TO HRE DESIGN

From cognitive sciences, across music performance, the embodiment paradigm can be transferred to the industrial field for human-robot physical collaborative applications, in shared workspaces. Embodiment basic features derived from cognitive sciences are body ownership, agency and self-location. From the music field observation, the concept of interaction-based cognition involving observable patterns and hidden cognitive states allowed to expand the embodiment key elements to further descriptors linked to patterns, such as human expression and gesture, and to states, related to the cognitive architecture and the anticipatory capability. In industrial contexts, HR interaction has to be assessed under spatial-temporal and cognitive dimensions, revealed by mutual integration indicators concerning coordination, synchronization and reactivity for both the parties. After all, embodied music cognition suggests that bodily synchronization enables predictive and reactive capabilities, that can enhance HRC by making robots' actions more anticipatory and context-aware. Cognitive processes are, thus, shaped by physical interactions, and vice-versa, for both the human and the robotic partner. Figure 4 summarizes this path.

The integration of AI within collaborative robots enhances such interactions, through cognitive communication interface. Thus, the transition from symbiotic to proactive HRC systems remarked by Li *et al.* (2023) is enabled by the mutual integration design features, revealed as SMC, SCL, TC and SA high levels. However, when mutual embodiment elements are involved, an even higher form of collaboration can be achieved, the HRE, revealed by parameters describing the reciprocal and adaptive integration of the two partners. We recognize such HRE descriptors as: (1) *Cognitive Mindfulness*, involving memory learning and cognition in interaction; (2) *Embodied Awareness*, featured by bodily involvement, cues utilization and action anticipation; and (3) *Bidirectional Control*, detectable by entrainment, enactment and advanced communication).

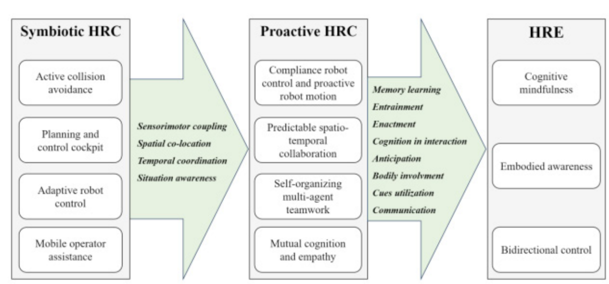

Figure 4. – Advancing HRC towards HRE

3.1 Cognitive Mindfulness (CM)

CM is meant as the capacity of humans and robots to maintain a state of focused, dedicated and adaptable cognitive state during their interaction to accomplish a collaborative task. It involves the ability to perceive, analyze, and adapt to the evolving dynamics of the HRC environment. A CM design goes beyond reactive responses of robots to human actions, and human's "automatic" gesture and re-actions to robot's inputs. Instead, CM defines the adaptive and proactive cognitive engagement between H-R, ensuring that collaboration is not just reactive but driven by continual learning (Ayub, et al., 2025). The higher the CM, the higher is safety, responsiveness, and the overall quality of interaction.

3.2 Embodied Awareness (EA)

EA refers to the bodily involvement, ability to catch, interpret and use partner's cues and to anticipate ongoing actions. We discussed how action can influence perception, as well as perception can influence action. Thus, the integration level of both patterns and states, merging physical sensations and cognitive processes, shapes the EA for both the human and the robotic partner. Human's EA can be enhanced by physical and cognitive learning techniques, such as Learning from Demonstration (Sosa-Ceron, et al., 2022), in combination with ergonomics design (Lorenzini, et al., 2023). From robot's side, EA relies on predictive models of human behavior, supported by advanced sensors that detect fine cues. For instance, the robot's capacity to sense and react to human force serves as a key indicator of its physical engagement in the interaction.

3.3 Bidirectional Control (BC)

Real-time BC involves the level of enactment, entrainment and advanced communication. Role enactment refers to the real-time and active realization of collaboration (Blaurock, et al., 2022), aware of partner's presence and control. Entrainment is intended as an evolved form of synchronization, where partners act in mutual feedback control involving advanced communication cues. Advanced communication refers to gesture-based communication, where both the human and the robot can express intentions and respond to each other through expressive actions. Basing on gesture studies in music performance, non-verbal cues such as ancillary gestures and movements, are relevant for shaping the collaborative process. Expressive gestures are meant as predictive indicators, *i.e.* observable patterns, revealing partners cognitive states and intentions. Thus, gesture-based control allows both parties to detect hidden signals and adjusting their own actions accordingly, in a human-like interaction style.

4. FINAL REMARKS AND FUTURE WORK

A higher degree of mutual interaction in collaborative tasks not only increases the likelihood of a successful outcome (Nikolaidis, et al., 2017), but also contributes achieving the Industry 5.0 goals (Van Erp, et al., 2024) in terms of the global sustainability (Rinaldi, et al., 2023). This paper proposes the HRE as an evolved dimension of proactive HRC, transferring principles of embodied cognition, across music performance observation, within the industrial field. The main advantage from HRE design is to expand the task performance measurement and management (Fantozzi, et al., 2023) to a higher level of analysis, where partners' mutual integration helps to predict future patterns and states for task effectiveness. Furthermore, gains in systems design, safety and control are evident: the deep understanding of HRC dynamics allows to designing anticipatory, responsive interactions, fostering greater efficiency and reliability, laying a foundation for more intuitive and flexible collaboration. The opportunity to design HRE enhances robots extend benefits to sectors where adaptability and predictive control are critical, *e.g.*, healthcare (Piffari, et al., 2022), logistics (Cimini, et al., 2022) and maintenance (Liu, et al., 2023).

ACKNOWLEDGMENTS

This work was partially supported by the Next Generation EU-Italian National Recovery and Resilience Plan (NRRP), Mission 4, Component 1, under the program PRIN 2022 PNRR of the Italian Ministry of University and Research. Project the grants from the MELODY Project - Multi robot collaborativE manipuLation suppOrting DisassemblY tasks - CUP C53D23008320001 - Code P2022XALNS.

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