Applications of Affective Computing in Human-Robot Interaction: state-of-art and challenges for manufacturing

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Abstract

The introduction of collaborative robots aims to make production more flexible, promoting a greater interaction between humans and robots also from physical point of view. However, working closely with a robot may lead to the creation of stressful situations for the operator, which can negatively affect task performance.

In Human-Robot Interaction (HRI), robots are expected to be socially intelligent, i.e., capable of understanding and reacting accordingly to human social and affective clues. This ability can be exploited implementing affective computing, which concerns the development of systems able to recognize, interpret, process, and simulate human affects. Social intelligence is essential for robots to establish a natural interaction with people in several contexts, including the manufacturing sector with the emergence of Industry 5.0.

In order to take full advantage of the human-robot collaboration, the robotic system should be able to perceive the psycho-emotional and mental state of the operator through different sensing modalities (e.g., facial expressions, body language, voice, or physiological signals) and to adapt its behaviour accordingly. The development of socially intelligent collaborative robots in the manufacturing sector can lead to a symbiotic human-robot collaboration, arising several research challenges that still need to be addressed.

The goals of this paper are the following: (i) providing an overview of affective computing implementation in HRI; (ii) analyzing the state-of-art on this topic in different application contexts (e.g., healthcare, service applications, and manufacturing); (iii) highlighting research challenges for the manufacturing sector.

Keywords

Human robot interaction, Affective computing, Human affective state, Manufacturing, Collaborative robot, Industry 5.0.

1. Introduction

In past decades, humans have been gradually ousted from manufacturing systems and automated factories improved capacity and efficiency in industrial production. Automation has allowed large quantities of goods to be produced at low costs [1]. This manufacturing paradigm has allowed an industry based on product standardization (mass production) to progress and expand [1]. However, with the development of markets based on mass customization (i.e., the manufacturing of small customized batches of products with short life cycles [2,3]), traditional automation may not be a viable cost-effective solution [4–6]. For this reason, hybrid automation in which human workers and collaborative robots (cobots) interact within production systems is emerging[7,8]. The in-depth study of the interaction between humans and robots is therefore of fundamental importance, especially to investigate possible new hazards from an ergonomic point of view (both physical and cognitive) [9,10].

Human-Robot Interaction (HRI) is a research field aimed at studying and improving interaction between humans and robots. The main characteristic of HRI is its multi-disciplinarity, primarily involving robotics, human-computer interaction, artificial intelligence, and social sciences [11]. In order to optimally design HRI applications it is necessary not only to focus on the technical aspects of the robot, but also to take into account the humans involved [12,13]. The analysis of aspects such as usability, workload, acceptability, and user's emotions is essential to obtain the full benefits from the interaction. In particular, the affective state of a person can play an important role in the success of the interaction or the performance of a task.

The introduction of collaborative robots in the industrial field is leading to a progressive elimination of fences between humans and robots. The combination of the capabilities of the robot, which provides power, precision, and repeatability, with those of the human, characterized by problem-solving skills and flexibility, leads to the creation of a new paradigm. The introduction of this paradigm, which represents one of the cornerstones of Industry 4.0 and 5.0, aims to make production more flexible, promoting greater interaction between humans and robots also from a physical point of view [14–16]. However, working closely with a robot may lead to the creation of stressful situations for the operator, due to the behaviour of the robot or some operations in a collaborative task [17,18]. Such situations can negatively affect the performance of the operator, also compromising his health in the long term. For this reason, the implementation of systems capable of monitoring and adapting to the cognitive and affective state of humans can help to create a healthier and more rewarding working environment for the operator.

With the recent development of intelligent manufacturing systems, capable of combining smart sensing, embedded technologies and data analysis to realize adaptive behaviors, industrial research on human factors is becoming increasingly relevant [9,19,20]. Design of human-centered adaptive production systems contributes to the creation of flexible working environments, able to adapt to the needs of individual workers considering the differences in their physical and cognitive abilities, thus improving human-machine interaction and the well-being of workers [21].

Affective computing is a research field focused on the development of systems able to recognize, interpret, process, and simulate human affects [22]. The term "affective state" concerns psychophysiological constructs (i.e. mental and physical processes) and refers to the experience of feeling the underlying emotional state [23]. Affective state of a human can be recognized through different modalities. The most used in affective computing are facial expressions, voice, body language, and physiological signals. In recent years, affective computing has also found application in HRI, especially in social robotics [24].

Socially intelligent robots can provide more significant support in different scenarios. As robots are becoming more common in our daily life, they are expected to interact and communicate with people according to human social behaviours and rules [25,26]. Thus, the robot capability to understand and recognize human emotions and intentions plays a fundamental role to provide practical and efficient support.

So far, several works on this topic have been presented, however only few of them are focused on the manufacturing sector. The main goals of this paper are the following: (i) providing an overview of affective computing applications in HRI through a quantitative analysis of the literature; (ii) analyzing the state-of-art on this topic in various application contexts; (iii) highlighting the research challenges for the manufacturing sector.

The paper is organized as follows. In Section 2, an overview on the use of affective computing in manufacturing is presented. Next, Section 3 provides the state-of-art of affective computing implementation in HRI in manufacturing and in other application contexts. Research challenges and prospects for manufacturing sector are discussed in Section 4. Finally, Section 5 covers conclusions and future work. The appendix contains the list of the main acronyms and abbreviations used in this paper.

2. Affective computing in Manufacturing

In order to study operator ergonomics in manufacturing settings, affective computing represents a valuable resource to overcome some of the main limitations of self-reporting tools. The use of affective computing techniques allows to obtain information about the human state in real time, without distracting him from his operations. In addition, it allows to obtain more objective measures related to the human state (e.g., stress, fatigue, and cognitive load).

The most common methods used in the literature to assess the human state in manufacturing involve physiological parameters, such as Heart Rate (HR), respiration rate, Electrodermal Activity (EDA), Electromiogram (EMG), and Electroencephalogram (EEG).

Ikuma et al. [27] explored the reliability of physiological responses (i.e., EMG and HR) to physical and psychosocial exposures in a simulated a manufacturing task. EMG was collected in order to measure muscle activity of the upper trapezius, middle deltoid, and anterior deltoid on the dominant side. HR was collected to account for fatigue and mental demand.

Purwandini Sutarto et al. [28] presented a novel study aimed at examining the effect of resonant breathing biofeedback training for reducing stress among manufacturing operators. Along with self-reporting tools, HR and respiration rate analysis allowed for tracking operator stress, providing objective feedback.

Attarchi et al. [29] assessed the relationship between shift working and occupational exposure to noise with blood pressure in a rubber manufacturing company. From the comparison between groups exposed to different levels of noise, it was noted that there was a significant difference in the ratio between people with normal blood pressure and those with hypertension. In particular, a higher frequency of hypertension was found in those exposed to more noise. This showed that constant exposure to high levels of noise causes greater stress on the operators, also having significant physiological repercussions.

Sutarto et al. [30] evaluated the effect of biofeedback training on the cognitive performance of operators in an electronics manufacturing industry. In the study, heart activity was monitored to assess stress generated during cognitive tests focused on assessing attention, memory, and cognitive flexibility.

Nakanishi and Sato [31] analyzed heart activity by Electrocardiogram (ECG) and brain blood flow in the right and left cerebral hemispheres by near infrared spectroscopy (NIRS) during an assembly task. The objective was to assess the stress digital manuals presented by a retinal imaging display (RID) on workers in the manufacturing industry.

Mauss et al. [32] focused on the association of work-related stress and various bodily dysfunctions in German industrial employees. In addition to taking periodic blood and urine samples and collecting anthropometric data in order to monitor worker health, Heart Rate Variability (HRV) was used to quantify stress.

Sedighi Maman et al. [33] proposed a data-driven approach for predicting occurrence and level of the physical fatigue using wearable sensors.

Argyle et al. [34] implemented a quality control inspection task in order to observe the physiological effect of increasing fatigue and mental workload . Physiological parameters considered included HR, breathing rate, nose temperature and hemodynamic response in the prefrontal cortex and middle temporal gyrus.

In the context of cloud manufacturing, Jiang et al. [35] proposed a study to investigate visual comfort of visual display terminal interfaces. The assessment of visual comfort was based both on subjective responses and EEG data.

Arpaia et al. [36] designed a single-channel EEG instrument for real-time monitoring of worker stress. The main innovation consists in the proposal of a non-invasive, easily wearable EEG instrument that addresses manufacturing constrains.

Another tool used to study human behavior in manufacturing is eye-tracking, which allows eye activity to be monitored to assess operator attention and mental workload.

Wu et al. [37] carried out an experimental study on human–machine interface in LED manufacturing systems to measure the influence of information overload on user experience. Eye-tracking methods were implemented and eye-tracking metrics (e.g., time of first fixation and number of fixations before fixating the area of interest) were derived to assess mental workload.

Huang et al. [38] focused on the detection of cognitive hacking (i.e., a cyberattack that seeks to manipulate the perception of humans by exploiting their psychological vulnerabilities) in visual quality inspections through physiological parameters. In particular, eye-tracking and EEG data were collected to this end.

Van Acker et al. [39] implemented eye-tracking glasses in order to assess mental workload in manual assembly tasks of increasing complexity. The obtained eye-tracking data were used to identify a behavioral video coding scheme to detect mental workload.

In the next section, a state-of-art focused on affective computing implementation in HRI in manufacturing will be presented.

3. State-of-art of Affective Computing in HRI

In this section, the state-of-art on affective computing in HRI applications is analyzed, in order to understand the current state and find possible gaps of the research.

3.1. Data collection and dimensions of analysis

Articles and conference papers concerning the human psycho-emotional state in HRI have been selected through the Scopus database [40]. This database was chosen for two main reasons: (i) it is more accurate than Google Scholar database [41,42] and (ii) its coverage in the Engineering field is superior to that of the Web of Science, especially for emerging research fields [43].

Journal articles and conference proceedings published in the last 15 years (from 2006 to 2020) written in English have been taken into account.

Particular attention was given to the selection of keywords to be used in identifying relevant literature. The starting point was the topic-related keywords found on the IEEE keyword list [44].

Following the backward and forward search approach proposed by Webster and Watson [45], the list of keywords of the search query was expanded. To further reduce the presence of "false positives", the set of documents returned by the database has been manually cleaned. After checking title, abstract and content, the authors excluded papers that did not concern the comprehension of the psycho-emotional state of humans interacting with robots through affective computing techniques. Literature reviews and papers focusing just on robot emotion expression were also excluded.

The manual cleaning process also allowed to identify the articles with a specific application domain (context-oriented) and exclude those resulting in multipurpose contexts. The final number of papers considered was 430, of which 173 journal articles and 257 conference proceedings.

Finally, in order to provide a structured analysis, each article has been manually classified according to the following three analysis dimensions summarised in Table 1:

Table 1. Description of analysis dimensions and related categories.

Dimension	Category	Description
Sensing modality	Facial expressions	Affect detection through analysis of voluntary or involuntary movements of facial muscles
	Body language	Affect detection through analysis of physical behaviors (e.g., gesture, posture, gait, etc.)
	Voice	Affect detection through analysis of paralanguage (e.g., intonation, pitch, volume, etc.)
	Physiological signals	Affect detection through analysis of physiological responses (e.g., Heart Rate Variability (HRV), Skin Conductance Response (SCR), etc.)
Research objective	Human affective state evaluation	Studies whose main objective is to evaluate the affective state of people interacting with a robotic system.
	Development of affect detection models	Creation of models and methodologies to recognize affective state of people through different sensing modalities.
	Development of control and adaptation systems	Development of systems that allow robots to change their behavior according to users' affective state.
	Development of new robots and devices	Development of devices or robots capable of perceiving human affective state.
Application context	Manufacturing	Sector focused on the production and sale of products through material transformation processes.
	Healthcare	Sector focused on the maintenance or improvement of health via the prevention, diagnosis, or treatment of disease, injury, and other physical and mental impairments in people.
	Service applications	Sectors involving the provision of intangible goods (e.g., tourism, education, entertainment, hospitality, foodservice)

3.2. General overview

The overview proposed in this section highlights the differences between the dimensions of the analysis in each context (see Table 1) and provides useful insights to anticipate future development directions.

The sensing modalities most commonly used to detect affective state are the following [24]:

- *Facial expressions* are the result of the contraction of facial muscles. These movements can be voluntary or involuntary and, in conjunction with eye movements, allow to convey an individual's affective state [46]. The detection of the affective state takes place through the analysis of data obtained by image acquisition systems, such as cameras. Moreover, the acquisition of affective state through facial expressions is usually not invasive, as it does not require to apply sensors on the individual.
- *Voice* is another medium to convey affective state. Through the analysis of paralanguage, it is possible to detect the affective state of an individual [47,48]. Paralanguage is the vocal component of language composed of elements that disregard verbal content, such as intonation, pitch, volume [49,50]. Detection of voice is usually performed using sensors like microphones.
- *Body language* is a form of non-verbal communication in which physical behaviors (e.g., gestures, posture, and gait) are used to convey information. Body language plays a fundamental role in everyday communication, conveying 55% of the information [51]. It is also used to communicate affective states voluntarily or involuntarily. Given its essential role in communication, body language provides useful information to understanding an individual's internal state. The detection of an individual's affective state through this modality is usually performed using cameras or motion sensors [52].
- *Physiological signals* represent another modality to estimate an individual's affective states. Human affective state is able to influence the whole body, generating physiological responses such as changes in heart rate, respiratory rate, muscle tension, or skin conductance [53,54]. The evaluation of these physiological signals can provide useful information about an individual's affective state, even outside conscious awareness. Indeed, one of the main advantages of the analysis of this sensing modality is the possibility of identifying subconscious affective states. Another advantage is that, unlike other sensing modalities, individuals cannot manipulate the activities of their autonomic nervous system, which carries out automatic processes. For these reasons, physiological signals are well-suited to measure anxiety and mental strain [55]. Depending on the physiological channel of interest, there are different methods to detect

physiological signals. For instance, hearth rate can be measured through electrocardiography (ECG) or photoplethysmography (PPG), muscle tension through electromyography (EMG), brain activity through electroencephalography (EEG), and electrodermal activity (EDA) with a skin conductance sensor [53,54]. These methods usually involve the use of wireless wearable sensors, which are suitable for real-time monitoring of affective state during HRI [24,56].

The main research objectives of the papers in this field can be classified as follows (see Table 1):

- *Human affective state evaluation* includes papers focusing on the analysis of affective state during the interaction with a robotic system. This type of analysis provides useful insights into, for instance, the effectiveness of certain therapies, the perception that people have on certain services offered by a robot, or the fatigue caused by interaction.
- *Development of affect detection models* considers articles where innovative models for affective state detection are presented to be integrated into a robotic system. These models, developed primarily through machine learning techniques, seek to overcome challenges and limitations arising from applied contexts (e.g., noisy and uncontrollable environment, affect detection of people with impairments or certain characteristics).
- *Development of control and adaptation systems* involves papers introducing novel robot behavior adaptation systems based on the human affective state. Depending on the application context and the purpose of the interaction, different types of behaviors which the robot can adopt are explored, attempting to make HRI as natural as possible.
- *Development of new robots and devices* concerns papers presenting affective robot prototypes or hardware/software systems for detecting affective state. These systems are developed with specific characteristics that allow to deal with particular situations arising from the application context (e.g., systems for tacking the operator's affective state of during a collaborative task in a factory, or affective robots with soft components for interaction with children).

Figure 1 shows the proportion of papers for three different application contexts. A significant number of papers can be found in the healthcare (59%) and service applications (36%) contexts, while manufacturing (5%) is still in an embryonic phase. In healthcare and service applications, the interaction with people plays a fundamental role, making the implementation of affective computing techniques in these contexts more natural. In manufacturing, on the other hand, the main value proposition is a product and over time more attention has been focused on improving production processes. However, in recent years, with the introduction of the concepts of human-centered manufacturing and Human-Robot Collaboration (HRC), the affective state of operators involved in production processes is becoming more relevant.

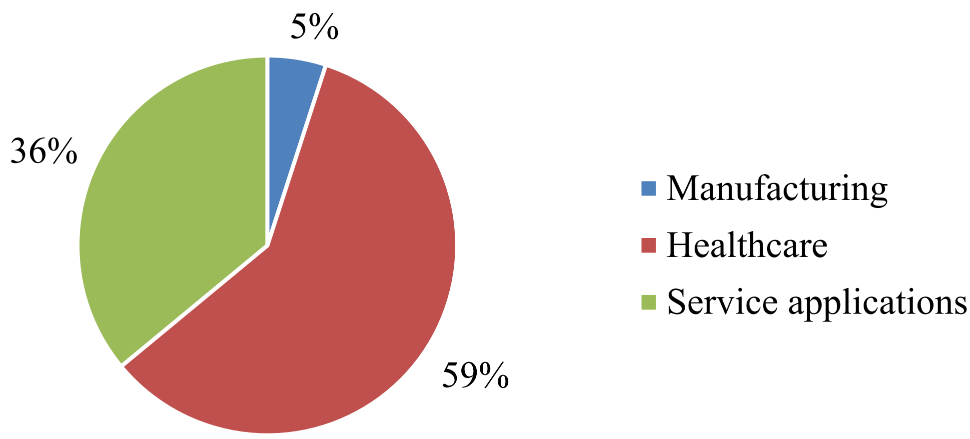

Figure 1. Proportion of publications found in the literature review for each application context.

Having provided a broad "picture" of the scientific literature concerning affective computing implementation in HRI, it is important to analyze the state-of-art. In the next subsections, relevant and recent works in the manufacturing and in other application contexts will be reported. This overview may contribute to better understand the current advances in the research field and to identify some possible challenges.

3.3. Application of Affective Computing in HRI: manufacturing context

Manufacturing is one of the contexts in which robotics systems are widely used [16,57]. However, as pointed out in Section 3.2, it is also the context in which affecting computing is still struggling to be implemented. Given the limited number of scientific contributions related to this sector, this section will try to provide a comprehensive picture of affective computing applications in industrial HRI scenarios.

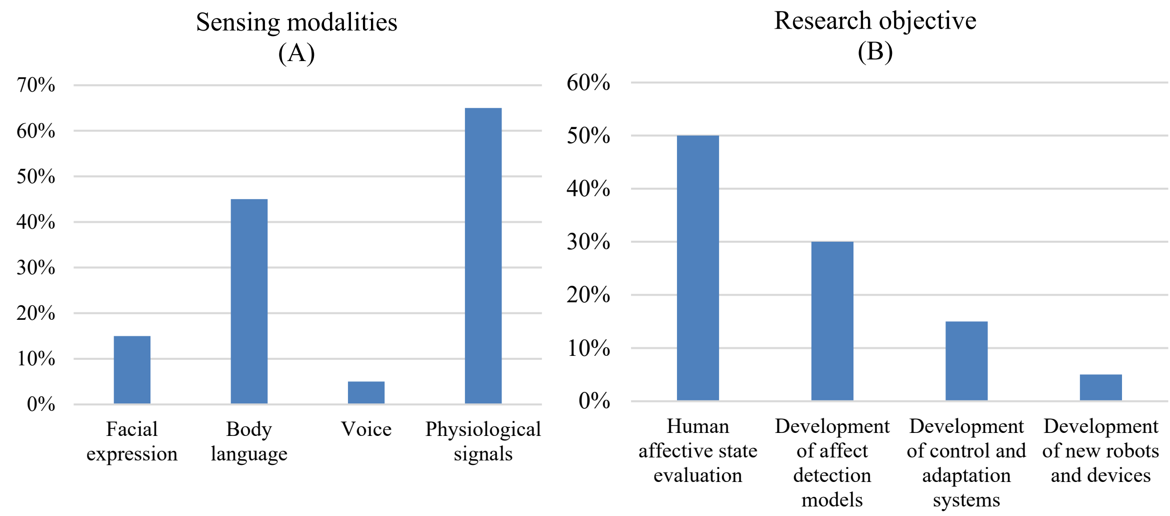

Figure 2. Sensing modalities usage proportions (A) and research objective distribution (B) in manufacturing context.

Fig.2.A shows the sensing modalities usage proportions in the manufacturing context. Most articles used physiological signals, followed by body language and facial expression. This might be due to the fact that operators often have to move during various operations and monitor their affective state through physiological signals (e.g., EDA, HRV) is an excellent solution. Monitoring through facial expressions and body language requires the use of a vision system, which can be suitable in situations where the operator's movements are rather limited. Voice is the least implemented sensing modality. One explanation could be that factories are often noisy environments where verbal communication can be difficult.

Fig.2.B shows the research objective distribution in the manufacturing context. Although there are not many papers published in this context, it can be seen that most focused on the evaluation of the human affective state. This highlights the growing interest in recent years in aspects of psychological ergonomics involved in HRC. Very few papers dealt with the development of new robots and devices in this context. In particular, to the best authors knowledge, no affective collaborative robot prototype has yet been developed in an industrial setting. This fact highlights a still embryonic technological maturity in the manufacturing sector, with respect to healthcare and service application contexts. Some possible reasons are the following: (i) only in the last decade the operator's psychophysical wellbeing is gaining more attention through the concepts of human-centered manufacturing and Industry 5.0, since traditionally robots have been introduced in industries mainly to make production processes more efficient; (ii) several industrial tasks in which robots are involved can introduce safety issues for the operator (e.g., handling heavy, sharp or dangerous objects, welding, and blasting), thus placing limits on HRC that only in recent years are being overcome.

Tab.2 provides a summary of some of the most relevant and recent works dealing with affective state in HRI in the manufacturing context. The first contributions in this field focused on the study of the operator's affective state induced by different movements of a robotic manipulator by analyzing physiological parameters [17,56,58]. Among these contributions, some also proposed models to automatically detect operator's state through physiological signals, such as HRV, EDA and EMG [56,58,59]. These models have subsequently allowed the development of robot adaptation systems, such as pre-collision strategies that consider the operator's affective state [60].

Later works analyzed user's state during the performance of industrial tasks with a robot. Some works analyzed the effect on the operator of different trajectory and speed profiles during a pick&place task [61,62]; others developed support systems for teleoperation based on operator's stress level [63].

Some recent contributions have used Virtual Reality (VR) to study user's affective state during interaction with industrial robots [64,65] and to evaluate affect-based control strategies for multiple robots [66]. Since the implementation and verification of collaborative tasks can require a considerable investment of resources, VR is a valuable tool to simulate HRC in a safe and cost-effective way.

Some pioneering works focused on the development of a bioinstrumentation system to measure stress levels of operators involved in HRI [67–69]. However, to the best authors' knowledge, there are no works in the literature that have proposed new industrial robot prototypes able to recognize operator's affective state.

The contributions reviewed in this section provide some insights into the application of affecting computing in manufacturing contexts. However, they also provide a picture of a still embryonic research field. In this view, the next section will show possible research challenges to be addressed by academics and robot industry.

Table 2 - Summary of papers considering affective state in HRI in manufacturing context.

Main research objective	Reference	Content	Elements of novelty	Open issues (future work)
Human affective state evaluation	*Kato et al.* [18]	The mental strain induced by movements of an industrial robotic arm is evaluated by analysing physiological parameters and subjective assessments. Skin Potential Response (SPR) is selected as physiological parameter for the evaluation. An experiment is carried out in which a robotic arm moves in front of the participants.	• Assessment of mental strain induced by HRC though physiological responses.	• Increasing the number of participants for more reliable results. • Conducting studies with other experimental settings.
	Kühnlenz and Kühnlenz [62]	The impact of various industrial robot trajectory profiles on physiological responses, namely HRV and SCR, is addressed. The results show that minimum-jerk trajectory significantly reduced HRV, implying significant stress reduction.	• Comparison of different trajectory profiles in terms of emotional stress reduction.	• Comparing different velocity profiles. • Increasing number of participants.
	Kühnlenz et al. [61]	The impact of different velocity profiles on HRV and SCR is assessed. The velocity profiles considered were linear and trapezoidal. The linear velocity profile produces a significant reduction of both HRV and SCR compared to the trapezoidal one, implying less stressful situation.	• Comparison of different velocity profiles in terms of emotional stress reduction.	• Investigating long-term impact. • Exploring other application scenarios.
	Etzi et al. [64]	The effect of the velocity of an industrial robot arm on the human's responses is analyzed. The experiment consists of performing a simple assembly task on a virtual platform with two different robot velocities. Participants' right arm movements and gestures are tracked. Physiological signals are also recorded, namely HRV and SPR.	• Assessment of the human psychophysical stress in HRC using Virtual Reality (VR).	• Comparing results on real interactions with physical robots.
	Fratczak et al. [65]	Different HRI situations are simulated on VR to study the influence of actions of an industrial dual-arm robot on human behaviour. The experiment consists of a pick&place task and involved 32 participants, collecting self-reports and recording their movement data, ECG and breathing waveform. The results showed that the robot's behaviour has a significant impact on operator's posture, focus and trust.	• Study of human responses to different HRI hazards using VR.	• Investigating long-term human behavior. • Comparing results with real-life situations.
Development of affect detection models	*Kulić and Croft* [58]	A fuzzy inference system is developed to estimate human affective state in real-time. Affective state is estimated using the two-dimensional valence-arousal representation. The level estimations of valence and arousal are based on the analysis of several physiological signal, namely ECG, SCR, and EMG of the corrugator supercilii (eyebrow) muscle.	• One of the first studies that estimates the affective state induced by an industrial robot through physiological signals.	• Identifying other physiological signals for valence estimation. • Improving the detection model.
	Kulić and Croft [56]	A new system based on Hidden Markov models (HMMs) for estimating human affective state in real-time is presented. Inputs of the models are several physiological signals (ECG, SCR, and EMG of the corrugator supercilia muscle) and affective state is estimated using a two-dimensional valence-arousal representation. The new HMM-based affect-detection system achieves overall better classification performances compared to the previous fuzzy inference system.	• Substantial improvement of a previously proposed affect detection model.	• Exploring the combination of the previous fuzzy inference system with HMMs. • Investigating relationship between EMG responses and robot movements.

	Moualeu et al. [59]	Presentation of a methodology for creating a model to measure human endpoint stiffness levels using operator's EMG data for haptic control in physical HRI. EMG signals from two different pairs of antagonistic muscles (biceps brachii/triceps brachii and flexor carpi ulnaris/extensor carpi ulnaris) are collected to determine which pair best explains endpoint stiffness. SVM classifiers are used to analyze EMG signals.	• Estimation of endpoint stiffness level using EMG for physical HRI.	• Implementing the methodology to adapt robot behavior according to operator's state.
Development of control and adaptation systems	*Kulić and Croft* [60]	An HRI pre-collision safety strategy integrating human affective state is proposed. By monitoring environment, physiological signals and human posture and position, the system allows the robot to change trajectory and speed to avoid possible collisions. The integrated system is implemented and tested in some experimental HRI scenarios.	• Development of an HRI pre-collision strategy considering also human affective state.	• Implementing and testing the system in real-life scenarios.
	Landi et al. [63]	An affective adaptation system for industrial robot teleoperation is presented. The experimental HRI scenario consists of a user teleoperating an industrial robot in a pick&place task. Operator's mental workload is monitored through HRV.	• Development of an affective control strategy for teleoperating an industrial manipulator.	• Testing the adaptation system on more complex tasks. • Including additional sensing modalities.
	Villani et al. [66]	An affect-based adaptation and control system for multiple mobile robots is presented. This system enabled an operator to interact with robots through a wrist device, which tracked wrist movements and stress. Wrist movements are used to teleoperate the robots, while stress is detected by HRV monitoring. When the stress state is detected, the behavior of the robots changes to relieve the operator.	• Affective adaptation strategy for human-multi-robot interaction.	• Investigating whether disengagement, boredom and tiredness affect HRV. • Implementing multi-modal interaction exploiting speech inputs.
Development of new technologies	*Itoh et al.* [67]	The bioinstrumentation system WB-1 is presented. This wearable system is able to measure arms movements, heart rate, respiration, EDA, pulse wave transit time, and blood pressure. Experiments are carried out to evaluate the accuracy motion capture system and show how to measure human stress.	• New wearable system to track different human parameters during HRI.	• Confirming whether humans feel unpleasantness by wearing WB-1
	Zecca et al. [68]	A new bioinstrumentation system, called WB-2, is presented. This new system represents the evolution of WB-1 and introduces new features, among which the possibility to track head and hand motion. A comparison between WB-2 and WB-1 is carried out.	• Upgrade of the previous wearable system WB-1.	• Making completely wireless the wearable system for experiments outside the laboratory. • Increasing the modularity of the system.
	Al-Yacoub et al. [69]	A hardware and software framework for a set of wearable sensors is developed to identify human psychophysical states (i.e., muscle fatigue, frustration, and anxiety) and to perform online classification of human intentions and activities during HRC. Data acquired via sensors include muscle activity, head movement, heart rate, nose temperature, and brain activity. The proposed hardware and software framework is also tested on a teleoperation task.	• Integration of several wearable sensors for HRC.	• Exploring different HRC applications. • Developing more efficient HRC systems.

3.4. Application of Affective Computing in HRI: other contexts

As highlighted in previous sections, healthcare and service applications are to date the most prevalent contexts for the application of affective computing in HRI. In these contexts, the deployment of social robots is becoming increasingly effective, thanks to the ability of these systems to interact with humans.

3.4.1 Healthcare

As highlighted in previous sections, healthcare is to date the most prevalent context for the application of affective computing in HRI. Social robots represent an important resource in healthcare, especially for taking care of the elderly, monitoring patients, and developing new treatment plans [70].

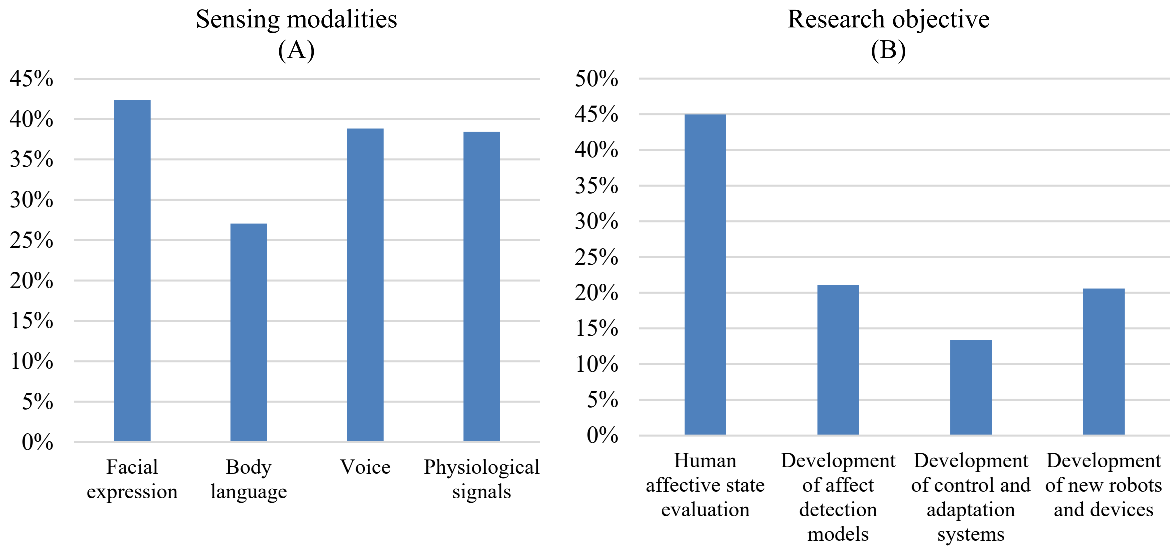

Figure 3. Sensing modalities usage proportions (A) and research objective distribution (B) in healthcare context.

Fig.3.A shows the sensing modalities usage proportions in the healthcare context. Facial expressions, voice, and physiological signals are the most implemented sensing modalities, followed by body language. Facial expressions and voice are the primary modes to communicate emotions in human-human interaction. However, there exist people who have difficulties in expressing their emotions in conventional ways, for instance, people affected by Autism Spectrum Disorder (ASD) [71]. In such cases, the analysis of physiological parameters plays an important role in understanding affective state, also helping to customize therapy sessions and improving their effectiveness [72].

It should be noted that the sum of the percentages in Fig.3.A is more than 100%. The reason is that in the literature some works implemented more than one sensing modality to perceive an individual's internal state. Combining information of two or more sensing modalities has several advantages, among which enhancing the robustness of the results and compensating for weaknesses in sensing modalities.

Fig.3.B shows the research objective distribution in the healthcare context. It can be observed that most of the papers (45%) focused on the evaluation of human internal state during HRI. This is due to the presence of several papers presenting case studies aimed at evaluating the effectiveness of specific therapies involving robots. It is interesting to note that a significant number of papers (21%) dealt with the development of and new robots and devices, highlighting a gradually growing technological maturity and significant interest in implementing affective robots in healthcare.

The implementation of social robots in the healthcare context is becoming popular especially in in long-term care facilities. The adoption of social robots represents a valuable support to help elderly people to remain healthy and received special attention over the years [73–75]. Several articles have shown the positive effects of interacting with affective robots, helping elders feeling considered [76], maintaining social relationships [77], improving their physical and mental health [78,79].

Several works investigated the use of affective robots in the treatment of different types of patients, such as children with ASD [71,80–82], People with Dementia (PwDs) [83], and stroke patients [84]. The results of these works have highlighted how the implementation of affective robots in therapy plans positively influences patients, increasing their motivation and engagement.

3.4.2 Service applications

With the gradual emergence of the Internet of Things (IoT), there is a strong interest in investigating what roles robots can play in society and how people perceive them. For effective integration, service robots need to be able to handle unexpected situations in unstructured places. Moreover, they need to be socially intelligent, i.e. able to fully understand the context and the people they interact with [85].

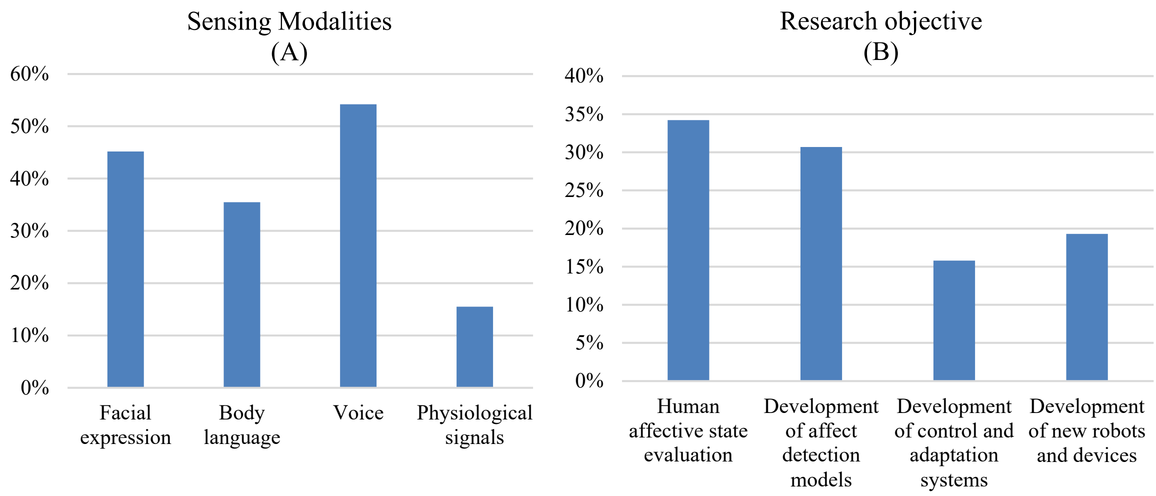

Figure 4. Sensing modalities usage proportions (A) and research objective distribution (B) in service context.

Fig.4.A shows the sensing modalities usage proportions in the service context. The most implemented sensing modalities are voice and facial expression, followed by body language. In human-human interaction, face-to-face and verbal communication are the inherently natural ways in which affective information is communicated [86,87]. Similarly, in the service sector, a robot needs to be able to establish the most natural possible interaction with people, understanding their affective state. Physiological signals are the least implemented modality in this context. This is due to the fact that in most cases the interaction takes place with bystanders and the use of sensors on these people is not always possible, significantly limiting the physiological signals that can be monitored.

Fig.4.B shows the research objective distribution in the service context. It can be observed that several papers focused on the evaluation of human internal state during HRI and the development of affect detection models (34% and 31%, respectively). Analyses of this kind are critical to understanding the acceptance and effectiveness of robots in various settings, including education, foodservice, hospitality, tourism, retail and entertainment. Moreover, in such contexts interaction often takes place in public places, where it is difficult to have complete control over the environment, generating several challenges in creating artificial intelligence models capable of handling unexpected situations.

It is worth noting that a consistent number of papers (19%) focused on the development of new robots and devices, highlighting a gradually growing technological maturity and significant interest in implementing affective robots in service applications.

Several contributions focused on the introduction of social robots in education and entertainment for children. Some studies examined the effects on students of robot lectures [88] and how different ways of presenting a robot can affect children's learning processes [89]. Child-robot interaction is a topic of particular interest [90], where the role of affective robots as playmates is also investigated [91]. Affect-sensitive robotic game companions allow to establish more engaging interactions with children, representing a valuable resource for learning new games, such as chess [92].

The use of small Unmanned Aerial Vehicles (sUAVs) in public spaces for delivery, crowd control, rescue and entertainment is becoming increasingly common. For this reason, there is a strong interest in studying and improving the interaction between humans and sUAVs [93].

Some works investigated behavioral strategies for affective robots in public places, such as information points [94], pubs [95], restaurants [96] or shops [97]. In these contexts, service robots are expected to respond appropriately to clients' behavior and engage them in stimulating experiences.

4. Research challenges for manufacturing sector

In manufacturing, the implementation of affective computing techniques in HRI is currently rather limited compared to other sectors, such as healthcare and service applications. One reason may be due to the different centrality of humans. In healthcare and service applications, the human interacting with the robot plays a central role. The robotic system is developed with the aim of creating a relationship with the subject in order to improve the effectiveness or experience of a particular service. On the contrary, in manufacturing, performance and productivity have always played the main role in the choice of production technologies, relegating the emotional state of the operators to a marginal importance. However, in recent years, there has been a growing attention to emotional ergonomics in various sectors, where the psychological state of workers is taken into account and solutions capable of improving the working environment are designed[98]. The novel Industry 5.0 paradigm provides a vison of industry that aims beyond efficiency and productivity as the sole goals, and places the well-being of the worker at the centre of the production process [99].

To better support the operator in complex scenarios, a major gap still needs to be filled: cobots should be endowed with proper socio-cognitive processing skills and shared autonomy capabilities. That way, robots will be able to proactively take over some tasks and relieve the operator's physical and cognitive load. In this sense, we can say that the development of collaborative robotic systems with the ability to adapt dynamically to the operator's state is still in its infancy [66,100]. The development of new affecting computing technologies in manufacturing can lead to the creation of solutions able to improve both the production performance and the operators' well-being.

A certain consequentiality can be noted among the four research objectives considered in the review section. The development of new affective robots requires the development of an adaptation system. In turn, the development of an adaptation system requires studies that evaluate the effect of different robot behaviors and the creation of models for affect recognition. This consequentiality can be used to create an overall roadmap for the development of collaborative affective robots for manufacturing (Figure 5).

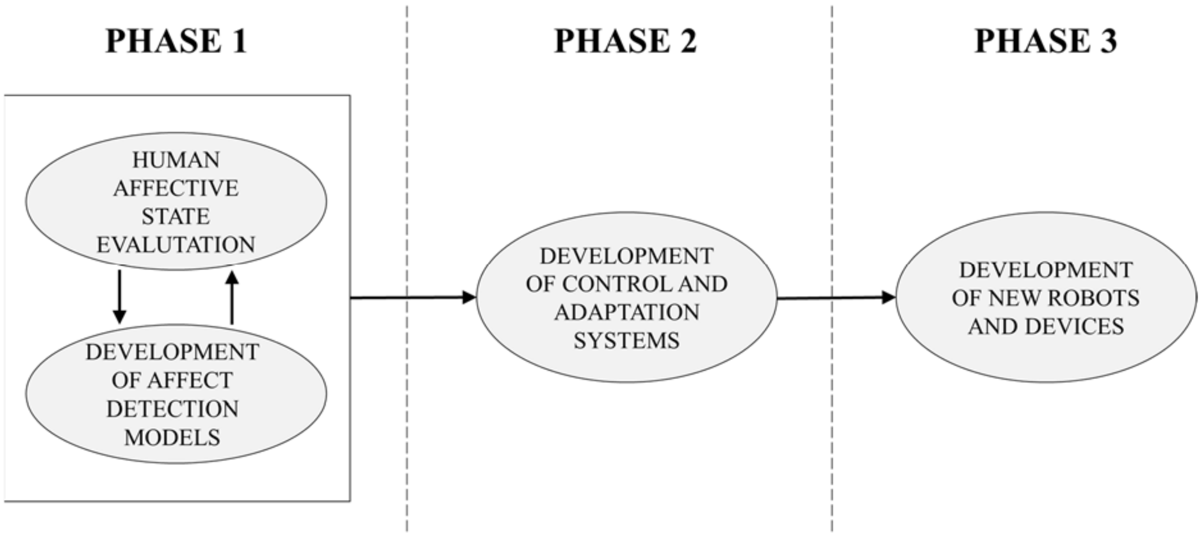

Figure 5. Overall roadmap for full implementation of affecting computing in HRI in manufacturing sector.

As a result of the state-of-art investigation reported in Section 3, a set of potential research challenges for manufacturing have been identified. These challenges were conceptualized through the analysis of: (i) advances in different sectors; (ii) open issues in different sectors; (iii) specific requirements of the manufacturing sector.

The research challenges for manufacturing are reported in Table 3 with also some references to papers addressing similar issues in other contexts. This information may serve as useful reference and guiding means for future research.

Table 3. Research challenges concerning the development of recognition models and affective state evaluation (Phase 1) in manufacturing context.

Development phase	Research challenge for manufacturing	Related papers in other contexts
1. Development of recognition models and affective state evaluation	Recognition of factors influencing the psychophysical state of the operator during collaborative industrial operations	[71,93]
	Exploration and selection of sensing modalities for different industrial contexts	[74,83,90,91]
	Development of methodologies and models to overcome sensing modalities limitations	[74,82,94]
	Conducting studies on operators' affective state in different real industrial HRI scenarios	[77,91,94]
	Carrying out HRI studies on affective state with immersive virtual reality systems	[101,102]
2. Development of control and adaptation systems	Identification of possible robot behaviours to improve the operator's well-being.	[76,92]
	Development of appropriate adaptation strategies for different industrial HRI scenarios.	[84,95]
	Development of online learning methods to customize robot behaviour to specific operators (*ad hominem*)	[103,104]
	Implementation of IoT and wearable technologies to enhance control and adaptation systems.	[85]
3. Development of new robots and devices	Development of affective cobot prototypes for different industrial contexts	[78,85,96]
	Evaluating and improving acceptance of new technologies for different industrial contexts	[78,79]
	Analysis of ethical and legal (e.g., data protection) implications of implementing affecting computing in industrial contexts.	[105,106]
	Development of solutions for real industrial applications (e.g., design-to-cost; fulfilments of stakeholders' requirements)	[85]

4.3. Phase 1: Development of recognition models and affective state evaluation

The first phase of the proposed roadmap is related to preliminary studies to develop collaborative affective robots in manufacturing context. Given the embryonic state of the research field, initial efforts should be directed towards the understanding how to develop affect recognition models and how to evaluate affective state in manufacturing contexts (Table 3). One of the first steps to be addressed is identification of the factors that most influence the psychophysical state of operators (e.g., robot speed and trajectory, level of experience, contextual and psychological factors such as noise and lighting, mental weariness, psychophysiological stress, and subjective representation of the robot). Understanding these factors is critical to develop adaptation models aimed at improving the well-being of the operator during HRC.

Manufacturing context is characterized by many different working environment settings, which vary considerably depending on production tasks. Each task implies different environmental characteristics that can influence the way humans and robots interact. For example, in a welding workstation it is likely to have a high noise level, a fairly high ambient temperature and a variable illuminance level, which may hinder HRI. Such environmental conditions may cause a limitation on the use of sensing modalities to detect the affective state of operators. For example, noisy environments may limit the use of voice; humid environments may affect the detection of physiological signals (e.g., EDA); personal protective equipment may cover part of the operator's face. These particular conditions pose multiple challenges in the development of psychophysical state recognition methodologies and models, the overcoming of which may allow a greater implementation of affective computing in manufacturing. Further experimental investigations are needed to identify the most suitable sensing modalities for different industrial contexts.

At present, most studies have focused on pick&place, assembly and navigation tasks. However, collaborative robots can be used for a variety of tasks, including, for example, welding, gluing, sanding, 3D printing, milling, polishing and pelletizing [16,107–109]. Furthermore, in most cases the applications of affective computing in HRI relate to the manufacturing sector in general, there is a lack of investigations focused on specific manufacturing sectors (e.g., semiconductor, automotive, aerospace).

Virtual reality allows simulating complex HRI scenarios with a modest use of resources. However, mainly exploiting vision, certain environmental factors characterizing some tasks may not be taken into account or are difficult to reproduce. Further research should focus on the creation and use of more immersive virtual reality systems, able to involve all the senses of the participant during a collaborative industrial task.

4.4. Phase 2: Development of control and adaptation systems

In order to achieve a symbiotic HRC, able to integrate human and robot's abilities, it is necessary:

1. collect and integrate different information about the context and the operator, including his affective state (e.g., fatigue, stress level).

2. develop robotic systems able to implement strategies appropriate to the situation.

For each industrial context, it is necessary to identify the behaviors that the collaborative robot can adopt and establish which are the most suitable to improve the interaction. Considering, for instance, a collaborative assembly task, the cobot might decrease its speed or change its trajectory according to the affective state of the human operator interacting with it.

It is important to understand in which situations the robot must change its behavior and which one to adopt in order to preserve the benefits of collaboration and operator's well-being. In this view, a crucial aspect to be addressed concerns evaluating whether the robot will have to proactively adapt its behavior to the changes in the operator's psychophysiological states (e.g., fluctuation of vigilance, degree of mental weariness, physiological stress level) or, instead, whether this modification should occur in response to a request from the operator. The behavioural strategy can be initially hard-wired based on the output of the operator's psychophysical state. However, further analysis should focus on the application of online learning methods (e.g., reinforcement learning), in which the operator becomes part of the learning/adaptation process by producing real-time feedback mediated by the psychophysical state detector. The implementation of *ad hominem* approaches might improve, production performance, operator well-being and cobot acceptance by operators.

Existing research recognizes the critical role played by communication to achieve a good synergy between cobots and human operators. Referring to other application sectors of collaborative robotics (i.e., service or healthcare), a considerable amount of literature has been published on these issues. The manufacturing sector, however, requires different approaches that merits further research. In this consideration, the creation of affective robot interfaces, i.e., robot control system interfaces able to adapt according to the affective state of the operator, for different industrial contexts, may represents a valuable challenge.

As manufacturing systems are increasingly becoming more geographically distributed (distributed manufacturing), further work is also needed to explore how information originating from different manufacturing contexts or sensors can be merged (i.e., data-fusion) and how they can be exploited for the development of optimal behavioral adaptation strategies and policies. In this perspective, trends related to the establishment of IoT and wearable technologies can be a development driver for increasingly high-performance adaptation systems [110].

4.5. Phase 3: Development of new robots and devices

The development of new technologies is a natural progression after the consolidation of the previous phases (Table 3). To this end, user-centered approaches should be employed.

The first step is the development of affective robotic system prototypes that optimally integrates the different hardware and software components (e.g., sensors, communication protocols, artificial intelligence algorithms, actuators). Considering the characteristics of each industrial sector, it is necessary to develop specific technological frameworks for various tasks, taking into account:

(i) reconfigurability of the system, in order to improve the usage flexibility;
(ii) non-invasiveness of sensors, to allow workers to operate without any constraints;
(iii) the user-friendliness of interfaces, to improve human-robot communication and fluency.

Prototype testing should be designed to demonstrate the effectiveness in reducing operators' cognitive load and improving their well-being. The synergy between research and industry could generate the development of living labs where users can participate directly in the development and validation of innovations.

As seen for other application contexts, an important aspect related to the development of new technologies concerns their acceptance by end-users. It is necessary to understand which factors influence acceptance and how it can be improved. Moreover, further experimental investigations are needed to compare the impact on operators' acceptance of traditional collaborative robotic systems and socially intelligent ones.

Special attention should also be devoted to the ethical and legal implications that can be generated by collaborative robots endowed with affecting computing algorithms. Modeling of the human involved in HRC is crucial to reach symbiotic collaboration. However, there are several issues related to the collection, storage and management of data generated by an operator (e.g., physiological, vocal, and facial data). Affective data should only be used to enable the robot to work effectively with the operator and protected using appropriates methods (e.g., blockchain). In addition, the operator should be given the freedom to decide when his or her emotional state can be monitored.

Finally, an important aspect is the transition from experimental prototypes to final solutions that can find an extensive use in real industrial contexts. For an effective deployment and implementation of new collaborative affective robots, in addition to meeting the requirements of potential stakeholders, it is important to pursue an efficient design-to-cost. This process requires the cost optimization of materials, components and features while preserving performances. In this view, the provision of product-related services may represent a strategy to accelerate and sustain the diffusion of affective computing technologies in manufacturing contexts [111,112].

5. Conclusions

This paper provides an overview of the implementation of affective computing techniques in HRI. Affective computing in HRI has been mainly explored in the healthcare and service contexts. Although the implementation of affective computing in manufacturing is still in an embryonic phase, in recent years it has been receiving more attention. This is mainly due to the gradual establishment of Industry 4.0, in which collaborative robots allow close interaction with humans sharing the same workspace. Both physical and psychological ergonomics of the operator must be taken into account to fully exploit the benefits of HRC. In addition, the collaboration between robots and humans needs to be as similar as possible to collaboration between humans. The adoption of collaborative robotics with greater empathy towards operators will allow to limit workspace alienation and support operators' well-being.

Understanding the mental and affective state of the operator allows robotic systems to be more context-aware and to provide support at the right time in different tasks. This ability is fundamental for the establishment of a symbiotic HRC in manufacturing. In this perspective, developing industrial robotic systems with social intelligence is one of the main objectives to be pursued.

In support of this aim, this paper proposed a detailed survey concerning the state-of-art of affective state in HRI in manufacturing The main elements of novelty and issues addressed by each paper on the topic has been highlighted and discussed. Being the study focused on practical applications of affecting computing in HRI in specific contexts, this study did not investigate general-purpose applications. However, this allowed for a greater emphasis on the distinctive characteristics of manufacturing compared to other sectors by pin-pointing the challenges addressed and the objectives.

With particular attention to the manufacturing sector, a roadmap for the full implementation of affecting computing in HRI has been proposed. This roadmap was developed taking inspiration from the research challenges addressed in other sectors and adapted to needs and goals of the manufacturing sector.

The roadmap's key-objectives highlight the need for greater integration between engineering, social, and life sciences. To this end, it will be necessary to develop multidisciplinary research projects capable of integrating researchers with different backgrounds and expertise.

Taken together, the findings of this study show that industrial robotic systems capable of adapting their behaviour to the psychophysical state of the operator are not "science fiction". Most of the necessary technologies and knowledge are already available. What is now needed is to take advantage of them, promoting an inclusive and human-centered manufacturing (Industry 5.0) culture.

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Appendix - List of acronyms and abbreviations

AC	Affective Computing
ECG	Electrocardiography
EDA	Electrodermal Activity
EEG	Electroencephalography
EMG	Electromyography
GSR	Galvanic Skin Response
HRC	Human-Robot Collaboration
HRI	Human-Robot Interaction
HRV	Hearth Rate Variability
SCR	Skin Conductance Response
SPR	Skin Potential Response