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Review

Human-robot interactions in manufacturing: A survey of human behavior modeling

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ABSTRACT

Human behavior, despite its complexity, follows structured principles. Better understanding the underlying concepts of human behavior in an industrial setting can help us to create more reliable and effective collaborative robotic environments. In factories, robots can interact with humans in unseen situations through sensing, processing, and predicting human behaviors. This work summarizes the efforts to express human behavior in industrial human-robot interactions (HRI) in manufacturing. For this purpose, all papers related to HRI in production systems, additive manufacturing, agent behavior, human cognition, cloud robotics, cooperative Markov decision process, multi-robot design, and collaborative robots are reviewed in this work. The discussion includes the existing methods, research gaps, and future research directions for envisioning a safer yet more efficient HRI practice. In detail, we discuss current research about human-centered HRI and robot-centered HRI based on the focus areas such as factorial analysis, predictive analysis, and control structures for social and/or industrial/manufacturing robots. In the last part, based on our findings, we report major limitations of the existing literature and propose future research directions such as cognitive modeling, perception development, interaction design, sensor-based control, and social effects in manufacturing.

1. Introduction

Robots are expected to have a more significant role in numerous aspects of our everyday lives, such as healthcare, education, entertainment, defense, and security in the near future [1–4]. Societies are undergoing numerous changes due to the rapid expansion of the robotics industry. While industrial robots can save energy, time, and resources by optimizing processes, service robots can change social constructs. Due to the inevitable co-existence of humans and robots in the coming years and the potential exposure of untrained end-users, robots should be enabled to deliver context-aware tasks.

While Industry 4.0 focuses on optimizing factories through promoting autonomy by relying on cyber-physical systems as well as internet of things and systems, Industry 5.0 is refining the interaction between humans and machines by refocusing on the human element. Many countries have offered strategic initiatives to implement Industry 4.0, and significant research efforts have been made to further develop Industry 4.0 concepts [5]. Industry 5.0 is defined to complement these efforts by using the creativity of human specialists in cooperation with effective, intelligent, and precise machines and robots [6], which further emphasizes the need to deliver appropriate, optimal, and efficient human-robot interactions (HRI).

HRI can be categorized into human-robot coexistence, cooperation, and collaboration as shown in Fig. 1 [7]. In the coexistence scenarios, the robots and humans will be dealing with unrelated tasks in completely separated spaces without having any contact. As a result, having context aware robots is not needed. In cooperation and collaboration scenarios, robots and humans share their workspace and work on related tasks. While in collaboration human and robot work on the same tasks, in cooperation scenarios the tasks are mainly linked through sequential steps. In addition, collaborative scenarios desire contact while cooperative ones are satisfied with any level of contact. Given the desire of having contact, it becomes critical to have context aware robots specifically in the collaborative scenarios.

Context-aware robotics is built upon the modeling of human behavior in HRI, as it has been shown that people's behavior changes while interacting with robots [1]. For example, Nomura et al. studied negative attitudes, anxiety, and communication avoidance behaviors because of attitude changes toward the robots' scale and robot anxiety scale [1]. Cummings M. presented a framework to relate skill-, rule-, and

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knowledge-based reasoning to expertise and uncertainty [8]. This taxonomy is designed to unify the conceptualization of all functional allocation for autonomous systems interacting with human decision-makers [8]. Since agents are likely to get stuck in sub-optimal solutions in complicated environments, Nguyen et al. used human learning strategies to adjust artificial agent behaviors in high-dimensional environments [9]. Huang et al. proposed a novel human decision-making behavior model for HRI to control multi-robot systems. The proposed human drift-diffusion model combined the traditional drift-diffusion model and the null-space-based behavioral control method by introducing a data-processing station and a human cognitive model [10]. As a result, robots must have precise knowledge about humans in different tasks to provide safer and more efficient interactions.

2. Materials and methods

In this review, our goal is to gather a detailed overview of human-robot interaction, focusing on human behavior and human decision-making in manufacturing. The methodology imbedded to select the recent literature developments concerning the topics of behavioral models for human-robot interaction is discussed here. We reviewed papers from 2000 to 2021 focusing on human behavioral modeling in HRI. Although the HRI literature is very limited between 2000 and 2016, there has been an increase of publications in this area since 2017.

The complete list of keywords used in this review includes HRI, human decision making, manufacturing, human behavior, human cognition, robot cognition, cognitive robot architecture, and human robot collaboration. This search led to a total of 410 papers. The selected papers were narrowed down to 108, focusing on the intersection of HRI and human behavioral modeling. An additional 20 papers were excluded as those were in a different language. Further examination led to exclusion of an additional 20 papers as those could not be applied to manufacturing. This review is concluded by examining the most appropriate mechanisms to be adopted for gaining better decision and behavior adjustment in human-robot collaborative environments. Furthermore, areas where a similar assessment of human behavior is required and challenges for such robots to overcome have been identified.

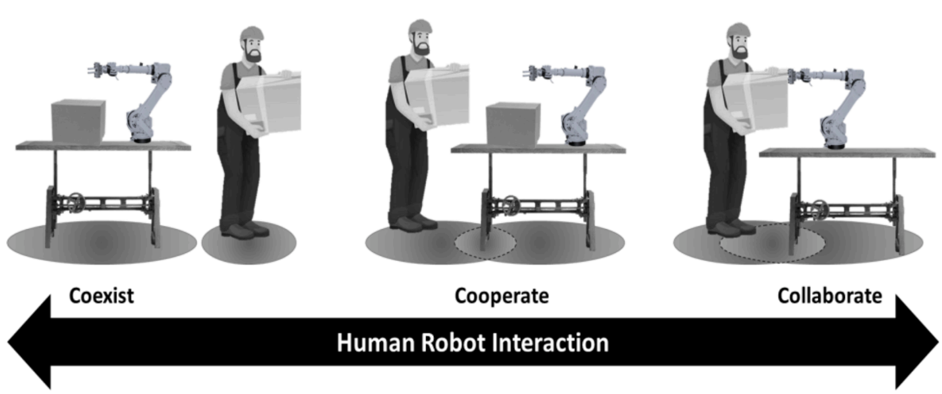
3. Results

One of the most ambitious long-term goals of robotics research has been developing robots capable of seamless integration in our daily lives. Therefore, recognizing, interpreting, and reasoning human behavior is a critical skill for a robot that co-inhabits the human environment and interacts with humans regularly. HRI, as a field of study, focuses on understanding, designing, and evaluating robotic systems to be used by or along with humans [11]. In manufacturing, robots have been deployed to replace or assist humans in performing repetitive or dangerous tasks [12]. Growing beyond assistance, not only do humans share their workspace with robots, but they also rely on them as collaborators [12]. As collaborative HRI becomes more prevalent, it is critical that robots understand human behavior and decision-making processes [13].

HRI literature can be divided into two main categories: Human-centered and robot-centered as displayed in Fig. 2. While human-centered HRI investigates issues such as the design and usability of proper interaction interfaces, robot platforms, and behaviors through extensive user studies, robot-centered HRI focuses on algorithms, engineering innovations, and other computational approaches that would improve the overall performance of the interaction [13]. What differentiates the human-centered and robot-centered HRI is the fundamental of the corresponding research. While human-centered HRI focuses on human cognition to develop better HRI, robot-centered HRI relies on better engineering the existing robotic capabilities to make seamless collaboration between humans and robots possible.

As displayed in Fig. 2, the arrangement of review for HRI in this paper categorizes papers into factorial analysis, predictive analytics, and control structures for social and industrial robots in both human-centered and robot-centered HRI systems. While factorial analysis focuses on identifying factors that impact the HRI from a human behavior perspective, the predictive analytics focus on better forecasting human behavior in HRI and control structures evolve on the ideas of better controlling robots considering humans' behavior. The distribution and trends of reviewed works across the years are demonstrated in Figs. 3 and 4, respectively.

Fig. 3a discloses most researchers (i.e., 43% of the reviewed works) rely on vision sensors. This can be attributed to versatility, reusability, and affordability of vision sensors, especially cameras. Visions sensors are followed by distance (21%), audition (10%), tactile (9%), force/torque (5%), motion (2%), and physiological (2%) sensors. Fig. 3b demonstrates that literature is more concentrated on robot-centered HRI (i.e., 71% of the published works) compared to human-centered (41%). Fig. 3c demonstrates control structures is the leading focus area (64% followed by factorial analysis (45%) and predictive analytics (24%). This well aligns with the fact that 71% of the reviewed papers



Space	Separated	Shared	Shared
Tasks	Unrelated	Linked	Shared
Contact	Impossible	Possible	Desired
Context Awareness	Not necessary	Minimal	Necessary

Fig. 1. Three levels of HRI and their characteristics [7].

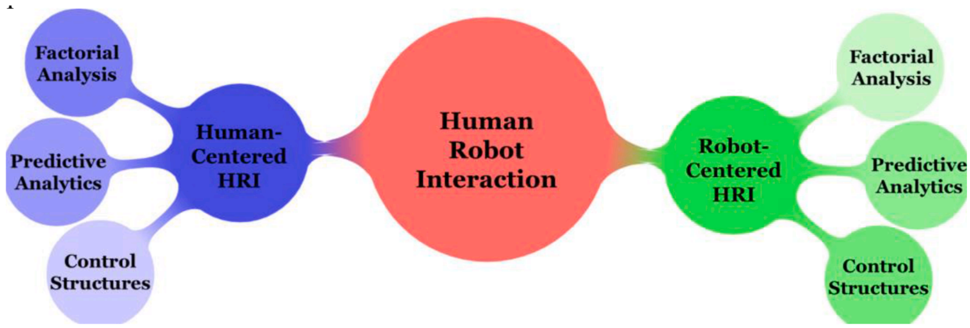


Fig. 2. Survey structure in this paper.

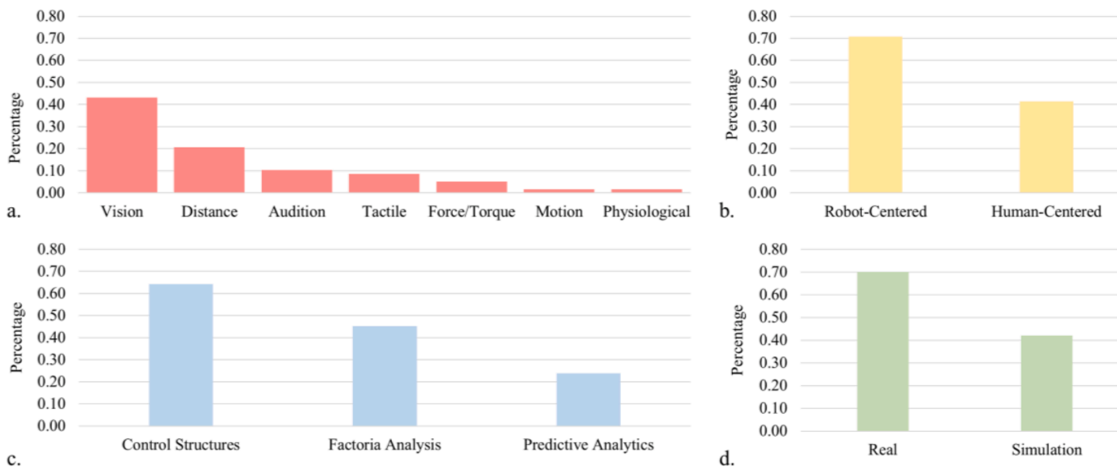


Fig. 3. The trends of sensor utilization (a.), research perspective (b.), focus area (c.), and validation technique (d.) in human behavior modeling in HRI.

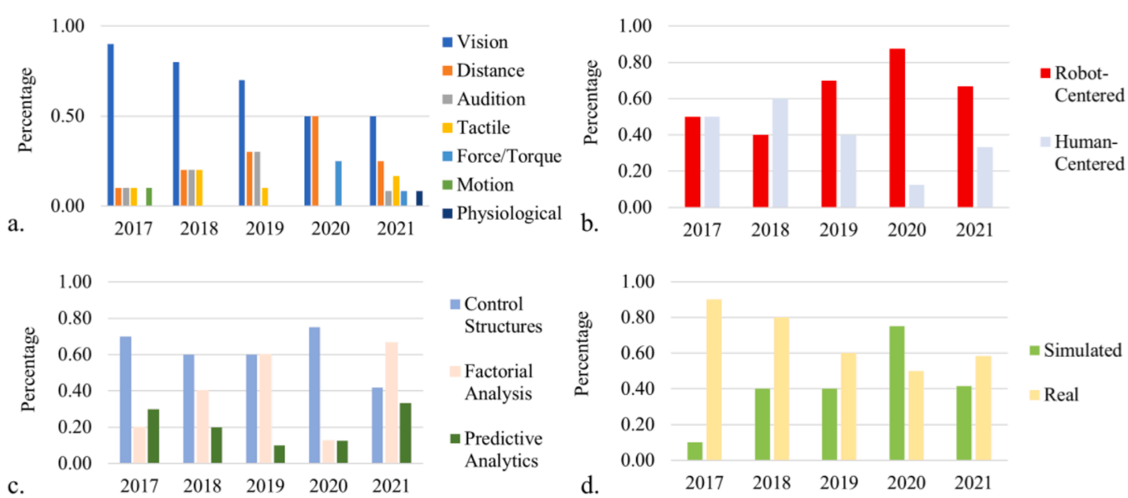


Fig. 4. The distribution of the reviewed papers based on sensor utilization (a.), research perspective (b.), focus area (c.), and validation technique (d.).

approached this research problem from the robot-centered perspective. As displayed in Fig. 3d, 70% of the reviewed papers relied on real robotic environment for validation their findings, while 42% of the literature depended on simulations. Fig. 4a–d demonstrate the distribution of the literature across years 2017 to 2021 in sensor, analysis perspective, application area, and validation technique, respectively.

Fig. 4a demonstrates a decrease in reliance on vision sensors over the years. This reduction can be a result of the decrease in sensor production cost over the last few years. The dominance of robot-centered HRI is displayed in Fig. 4b. Although some fluctuations can be observed over the years, the robot-centered HRI seems to be the leading perspective in human behavior modeling in HRI. As shown in Fig. 4c, while there have been some increases in research focused on factorial analysis, no certain conclusions could be reported on predictive analytics and control structures. Fig. 4d displays a decrease in using actual robots for validation purposes. This decrease can be caused by the advancements made in physics-based simulation modeling and emergence of game engines in manufacturing.

3.1. Human-centered HRI

3.1.1. Factorial analysis in human-centered HRI

Human-centered, also known as user-centered, HRI focuses on user perspectives and needs in a collaborative environment through studying aesthetic, operational, and social contextuality [14]. Masuyama et al. looked at human psychological phenomena in communication from the perspective of internal and external factors such as perception, memory, and emotional information [15]. Based on these, they developed an interactive robot system to support robot's decision-making [15]. Their experiment is based on processing multi-modal information to emotion model and also recognizing robot behavior [15]. Sanders et al. studied how trust and use choice are related in HRI [16]. In their experiment, human subjects were asked to rate robots on a trust scale and later to choose between completing a task using the assistance of the rated robot or a human [16]. Results demonstrated that although higher trust levels led to more robot usage, it was highly affected by the nature of the task in question [16].

To promulgate safe human-robot cooperation in a manufacturing setup with privatized human-robot cooperation and training, Tsiakas et al. suggested a cyber-physical system (CPS) solution [17]. Papanagiotou et al. provided five experiments to study the effects of gesture cognition and pose approximation on the cycle time and the range of the user's motion [18]. Buerkle et al. prepared an adaptive human sensor experiment, which combined objective, subjective, and physiological scales, and machine learning [19]. Tsiakas et al. conducted an experiment to recognize the minimum intrusive combination of sensors for efficient behavioral forecasting [17]. Urgo, Tarabini, and Tolio iused image processing to identify factors in workers' behavior to extract knowledge related to undergoing tasks via hidden Markov models to cataloging possible errors, deviances from the dangerous conditions in real manufacturing environments [20].

3.1.2. Predictive analytics in human-centered HRI

Pohlt et al. measured the effect of automated inputs, which led to a decreased capability in forecasting behavior and a loss of robustness of human-robot cooperation during gesture-based interaction [21]. To test the compatible behavior framework proposed by Buerkle et al., two assembly scenarios (manual and cooperative) were performed to predict realized workloads of human users [19]. Physical HRI assists an operator to go beyond the current capabilities of industrial robots via combining the user's cognitive capability with the precision and strength of robots [22]. Veselic et al. proposed a framework to help operators through active reactions to their orders based on the context and user awareness [22]. This additional layer of awareness strengthened the system in better identifying the purpose of an operator, avoiding false predictions, and assisting them in their tasks [22]. Liu and Wang proposed a new human-robot collaborative system design corresponding to the needs of having better understanding of human worker's intention in order to model product assembly tasks as a sequence of human motions with Hidden Markov prediction model [23]. Masoud et al, proposed a hand gesture recognition framework to identify the undergoing tasks by workers and evaluate the workers performances in pseudo real time using predictive analytics in line production of bio products [24].

3.1.3. Control structure in human-centered HRI

In the Masuyama et al. study, controlling the robot's behavior is based on robotic emotional model, associative memory, and also biometric data [15]. Klumpp et al. developed a human-computer interaction efficiency description in production logistics to address the management of workers in digital work settings [2]. Askarpour et al.'s research was a confirmation approach to analyze cooperative robotics applications safety with a rich non-definite formal model of user behaviors that obtains the dangerous situations resulting from human mistakes [25]. Kadar et al. prepared insights into the problems of automation and mixed vehicle controlling and about the theoretical and moral results of their limited knowledge of human performance issues [26]. Papanagiotou et al. researched the contribution of gesture cognition and pose approximation to the smooth introduction of cobots into an industrial assembly section with the human users and provided the action-reaction between them [18]. Moreover, operator safety and reduction of errors were highlighted, which led to the development of two control layers in the decision-making process [18]. Araiza-Illan et al. developed a dynamic safety solution for human-robot cooperation that follows human behavior based on RGB-D cameras [27]. Okuda et al.'s research suggested a design methodology for a switched assist controller for a human-machine collaborative positioning function that considers a new human behavior model based on a continuous/discrete hybrid dynamical set [28]. Dong and Naghdy delved into the possibility of reconstructing human manipulation proficiencies in intricate bounded motion by controlling, tracing, and learning the manipulation executed by the user [29]. Veselic et al. proposed a framework to improve traditional robotic control systems by adding context awareness through state space modeling and using time varying linear quadratic regulator (TV-LQR) [21]. Bian et al. developed a smart HRI control framework for small and medium sized manufacturers. In their work, a real-time monitoring system of manufacturing workflow for smart connected worker was developed which incorporated state-of-the-art ML-based methodologies such as finger detection and text recognition for 3D printer control as well as text recognition and object detection for machine state recognition, and Skeleton detection for user motion monitoring [30].

3.2. Robot-centered HRI

3.2.1. Factorial analysis in robot-centered HRI

Trust-aware HRI, as a subset of robot-centered HRI, builds upon the integration of trust dynamics and trust behavior models among the robot and human [31]. Guo et al. proposed a trust-aware factorial framework through identifying factors impacting robots' performance. Their proposed framework enabled the robots to estimate a human's trust, anticipate the impact of trust on their interaction, and maximize its objective by selecting actions [31]. Their experiments demonstrated that the modeling of trust could significantly impact the collaborative environment, where one trust model (i.e., reverse psychology) led to a robot manipulating a human's trust while the other (i.e., disuse) restricted such an outcome [31]. The conjoint impacts of communication and social conformity on trust in HRI were investigated by Volante et al. [32]. The results illustrated that although human social assessments had a heavier impact compared to direct robot communication, the conforming trust followed the group's trust [32]. Alarcon et al. have sought to remove these restrictions via a mixed factorial design to test the effects of trust on human-human and human-robot interactions over time with an assertion on anthropomorphic robots in a social outline [33]. Social robots must conform to group norms without telling robots how to act by group members [34]. Fuse et al. examined whether the robot system creates the decision criteria for obeying group norms by learning from interactions through reinforcement learning [34]. Quintas et al. designed an experiment based on multivariate analysis of variance, by analyzing the samples and concentrating on the analysis of the effects on specificity of various approaches [35]. Takahashi et al. studied the impact of emotional expressions on HRI [36]. Their experiment involved participants playing a game of a finite-iterated prisoner's dilemma with a small humanoid robot [36]. The robot could convey emotions through different expressions and actions (e.g., limb motions) [36].

Smith et al. consolidated human studies in motion, intention, and preference into a discretized human model (i.e., cooperative Markov Decision Process) that can readily be used in robotics decision-making algorithms [37]. Given the various and ever-changing robotics setups, awareness and context logic is important for gathering more effective service robots [38]. L. Villamar Gómez and J. Miura proposed a framework for service robots that incorporates ontological awareness logic and HRI to interpret natural language orders [38]. Moreover, they provided two distinct experiments in a simulated setup for analyzing human behavior and compared it with the robot's behavior [38]. Huang et al. proposed a new empirical robotic disassembly cell consisting of two cooperative robots and a human operator that can work with no risk in tandem for particular or parallel disassembly duties in a shared environment [39].

Chinchali et al. used a combination of procedure, control, and data mining algorithms addressing the proactive decision-making issue, enabling robots to decode human intent and use this knowledge for safety and task satisfaction [40]. First, they turned the trajectory of human behavior with high dimensions into accurate behavioral summaries [40]. Moreover, they leverage formal procedures to model high-dimensional agent goals and information-searching behavior with temporal logic formulas [40]. Tokody et al. provided the possibilities of applying cooperative robots during the process of automation in metalworking [41]. For illustrating the operation of the control interaction outline, Medina et al. provided a psychological examination with naive human operators [42]. Bockenkamp et al. measured the impact of robotic motion on humans during cooperative working sets and analyzed the impacts of robotic motion on human behavior [43]. Music and Hirche reviewed improvements in human-robot group interaction [44]. Panfir et al. designed an experiment in the manufacturing setting and provided a case study illustrating the assimilation of the human-like robotics set within a collaboration application [45]. The purpose of Chen et al. was providing a method of assembly scheme generation and selection for human and robot concordant (HRC) cell assembly with simulation and experimental results [46]. Zhang et al. studied welder behavior in torch adjustment as respond to weld pool by correlating welding torch tendency to weld pool surface [47].

3.2.2. Predictive analytics in robot-centered HRI

Sanders et al. studied how trust and use choice are related in HRI [16]. Results demonstrated that cooperative emotional expression by the robot improved cooperation from participants in Takahashi et al.'s study, and the prediction model were based on four prediction parts ("cooperative-competitive," gender, "friendly-estranged," and "grown-up-childish") [36]. S. Nicolas and W. Agnieszka measured contributors, demand for recognition and closure to predict perspectives on robots and anthropomorphic attributes on variant robots [48]. Qureshi et al. suggested a reinforcement learning outline in which an operator gains the inherent motivation-based rewards through the action-contingent predictable model. By using this method, the robot learned the social skills from the human-robot action reaction experiences collected in the uncurbed environments [49].

As short-term or midterm predictions have relatively long-time horizons to regulate, Khan et al. created a new vision-based action-reaction method [50]. For the safety of human operators during robot actions, Liu and Tomizuka predicted the human's future states [51]. Medina et al. provided a control framework for anticipatory haptic assistance where robot behavior adjusts for predicting uncertainty [42].

Quintas et al. created an outline to obtain the predicted behavior of the operator into descriptive situations and then translated these into an operator information model and used the results in probable planning and decision making to control HRI [35]. To increase acceptance of the robot by the users, Pérula-Martínez et al. suggested a decision-making framework based on bio-inspired notions, like incentives, drives and well-being that simplify the rise of natural behaviors. For controlling the decision-making setup, user's preferences are considered and change the homeostatic procedure.

3.2.3. Control structures in robot-centered HRI

Yun suggested a hybrid approach combining gaze control indicator and conceptual measurements for social signs for selecting an appropriate interlocutor of socially interactive robots in a situation interacting with more than two humans [42].

Controlling the robot's performance is closely related to improving the movement of robot [53]. For the implementation of cooperative tasks in hybrid assembly cells an intelligent decision-making method that allows human-robot task allocation was suggested and unified within a Robot Operating System framework by Tsarouchi et al. [53]. In most current manufacturing operations, autonomous robots are co-present along with human [54]. Decision-making prepares the robotic users with higher compatibility, by enabling its behavior to change according to available information, for both the robot and human associates [54]. Oliff et al. developed an approach to effectually model these setups using a reinforcement learning agent capable of autonomous decision-making [54]. Liu and Tomizuka checked the controller design model of environment sharing human-robot assembly groups and adopted a two-layer interaction method between the person and the robot [51]. Chen et al. suggested a virtual reality (VR) and Kinect-based immersive teleoperation set to connect and control the physical and virtual setup [55]. By evaluating the human behavior in assembling intricate parts, Kang et al. suggested a geometry-independent control methodology for robotic assembly using adaptive accordance method [56]. Chu et al. provided an optimization method for empowering the pre-planned approach by taking into consideration the uncertainty of human [57].

Mantegh and Darbandi provided a method for robot function planning by relying on artificial intelligence and hierarchical knowledge demonstration [58]. Music and Hirche reviewed improvements in human-robot group interaction focusing on control-sharing methodologies, human behavior modeling, level of autonomy, and human-machine interfaces [44]. In Bhalaji et al.'s study, a multi-criteria decision-making method, "Decision Making Trial and Evaluation Laboratory" was used to analyze and control the risk factors affecting human-robot interaction in the assembly task [59]. For position and torque control in the presence of indeterminacies changing constraints, Klecker et al. used a bottom-up approach to empower robust and adaptive learning methods for trajectory tracking [60]. Costa et al. created automated equipment capable of performing assembly functions, which coped with all the requirements in the market, and is more effective than manual stations [61]. Papageorgiou et al. developed a passive control scheme for helping kinesthetic rectifications of the learned behavior in task variations by engaging the utilization of penetrable spherical virtual fixtures around the dynamic movement primitives' that follows the human coaching's motion [62]. Table 1 reports the classification of the reviewed papers based on their research perspective, focus area, application, utilized sensors and validation technique.

4. Discussion: limitations and research opportunities

4.1. Limitations

In the reviewed papers, there are limitations that may have caused negative impacts on the results or distance the research from reality. For instance, some researchers validated their proposed approaches through not fully physics-based simulation instead of real experiments or more advanced simulations (e.g., [2,32,38,43,69,70]). Other limitations include lack of generality, such as conducting experiments limited to a specific robot (e.g., [1,36]) or case-specific definitions of human cognitive behavior such as trust and trust dynamics models (e.g., [31,48]), emotional expressions without considering personality traces (e.g., [32]), or temporally fixed human behavior modeling (e.g.,[32,48,63]). Computational efficiency is another limitation of the discussed works, where exponential growth computational aspects of the modeling restrict the performance of the proposed approaches or lead to oversimplification and loss of information (e.g.,[1,35,37,49,55,63]).

Table 1
A summary of the surveyed papers.

Ref.	Research Perspective		Focus Area			Application		Sensor							Validation Technique	
	Human-Centered	Robot-Centered	Factorial analysis	Predictive Analytics	Control Structures	*Manufacturing*	Social	Vision	Distance	Audition	Tactile	Force/ Torque	Motion	Physiological	Simulated Robot	Real Robot
1		✔		✔			✔	✔		✔						✔
2	✔				✔	✔			✔	✔					✔	
7	✔				✔	✔			✔						✔	
8		✔		✔	✔	✔		✔							✔	
9	✔				✔	✔			✔						✔	✔
13	✔		✔				✔	✔							✔	
14	✔		✔		✔			✔								✔
15	✔	✔	✔	✔			✔	✔								✔
16	✔		✔	✔		✔		✔		✔					✔	
17	✔		✔		✔	✔						✔				✔
18	✔		✔	✔		✔								✔		✔
19	✔			✔		✔		✔								✔
20	✔		✔			✔		✔								✔
21	✔			✔	✔	✔			✔						✔	
22	✔				✔	✔			✔							✔
23	✔			✔		✔		✔								✔
24	✔			✔		✔					✔					✔
25	✔				✔	✔		✔	✔							✔
26	✔				✔	✔		✔								✔
27	✔				✔	✔							✔			✔
28	✔				✔	✔						✔			✔	✔
29	✔		✔				✔	✔							✔	✔
30	✔		✔			✔		✔								✔
31		✔	✔				✔	✔							✔	✔
32		✔	✔				✔	✔								✔
33		✔	✔					✔		✔						✔
34		✔	✔		✔			✔		✔						✔
35		✔	✔	✔			✔	✔		✔						✔
36		✔	✔			✔		✔							✔	
37		✔	✔			✔		✔			✔				✔	
38		✔	✔		✔	✔		✔			✔					✔
39		✔	✔		✔	✔			✔						✔	
40		✔	✔			✔			✔							✔
41		✔	✔	✔	✔	✔						✔			✔	
42		✔	✔			✔			✔						✔	
43		✔	✔		✔	✔		✔			✔					✔
44		✔	✔			✔				✔					✔	
45		✔	✔			✔		✔							✔	✔
46		✔		✔			✔		✔							✔
47		✔	✔			✔		✔	✔							✔
48		✔		✔				✔	✔		✔					✔
49		✔		✔		✔		✔							✔	
50		✔		✔	✔	✔			✔					✔	✔	
51		✔			✔			✔								✔
52		✔			✔			✔								✔
53		✔			✔			✔								✔
54		✔			✔	✔		✔	✔						✔	
55		✔			✔	✔						✔				✔
56		✔			✔	✔			✔						✔	
57		✔			✔	✔							✔			✔
58		✔			✔	✔			✔							✔
59		✔			✔	✔						✔			✔	✔
60		✔			✔	✔		✔								✔
61		✔			✔			✔		✔	✔					✔
62		✔			✔	✔		✔				✔			✔	

4.2. Research opportunities

Although robots have greatly advanced over the last few decades, there is space for further improvements in the HRI spectrum with regards to easier interaction, context awareness, mobility, safety, and effectiveness of automation. In addition to addressing the aforementioned limitations, the following are the directions where further research can greatly impact the quality of human robot interaction or collaboration.

Cognition Modeling. To maximize the benefits of teamwork, it is essential to have complete understanding among the team members. This becomes more critical when the team is formed of different entities such as robots and humans. To address this challenge, explicit models of human behavior and decision-making should be developed. Aspects of human cognition such as trust have been studied by separate groups, but these efforts are usually aimed at a specific form of HRI or limited to a specific type of robot. As a result, there is a need to explore not only the modeling of trust but also address the effects of failure on trust in a more general context [64]. As there may be unlimited factors affecting trust, future research of trust modeling should focus on the development of general models based on measures instead of counting factors affecting specific cases or scenarios. The same arguments can be applied to other cognition modeling aspects such as emotion modeling and/or decision making. In addition, there are limited works on continuous self-learning robotic agents regarding human behavior [65]. Further research in this area not only enables better cognition modeling, but also enables personalized HRI experience for collaborating humans.

4.2.1. Perception development

Perception systems enable robots to grasp their surrounding environment through sensors such as cameras or external equipment such as touch screens. Perception methods range from machine learning and artificial intelligence to fuzzy logic models and statistical approaches. Yan et al. have reviewed the existing perception methods in detail [66]. A gap in literature is evaluation of the practicality of the proposed methods. In other words, the existing works focus on developing high performance and accurate solutions without studying the computational, implementation, and maintenance costs. Requirements such as low computational cost and autonomy are critical in developing perception methods for implementing seamless HRI and further research should be done in this area.

4.2.2. Interaction design

The design of any product or procedure can significantly impact its delivery and acceptance. Current research relies on existing interaction models and designs to build HRI. These interaction designs can substantially contribute to developing better behavioral models of how humans understand robots and their capabilities. There is a need to better model humans' understandings from robots and set the actual expectations of the robots' behaviors reasonably. For safer interaction modeling, further research should be conducted to better understand aspects such as timing in interaction, physical environmental, and communication modes. The existing metrics for measuring success in HRI are elemental as reported by [67] and cannot frame the complexity of human and robot relations. Further work in this area can discover insight into human expectations of HRI.

4.2.3. Sensor-based control

Although robotic control is a mature field, having many commercialized solutions already employed in the industry, not as many efforts have been implemented to regulate interaction and collaboration between humans and robots. To have a safe and collaborative environment, it is critical for robots to be aware of their surroundings. Sensor-based control is a flexible solution for HRI, as it enables perception to action in real-time. Sensors are the main requirement for establishing sensor-based control structures. Sensors are becoming more affordable and less hindersome to wear, making it easier to use them for better implementation of HRI. The sensors can be categorized into vision, audition, tactile, force, and distance groups. While vision and tactile are the most popular senses on HRI, the introduction of affordable and accurate distance, audition, and force sensors present great research opportunities. At the same time, although there is some research focused on enabling sensor-based control for each sensor group (i.e., vision, audition, tactile, and distance), the same cannot be said about cross group sensor-based control. In addition, newer topics such as traded control, shared control, or hybrid control, which are variations of sensor-based control, require further work [68].

4.2.4. Social effects

Although limited, there are some examples of research that have been discussed here, but a major shortcoming in the existing literature is the lack of studies on the social effect of HRI. In the HRI literature, the term "team" is usually limited to two single agents, one human, and one robot. While it may be true in many cases, it fails to study the impact of having multiple humans and robots in the team. Human behavior and decision-making can be significantly impacted when influenced by peers and friends. Similarly, the perception and sensor-based control of robots will be different when working with a group of humans and robots. For example, the use of task constraints has not been sufficiently explored when multiple robots are integrated to perform a specific task while collaborating with different humans [68].

5. Conclusion

Human-robot interaction is a fast-growing field of research with many applications. The field addresses ongoing challenges with the potential of providing solutions capable of significant social and industrial impacts. Due to its interdisciplinary nature, researchers are required to define their research within a broader context. The first key point is robots should become context-aware and capable of learning about human behavior, especially in terms of emotion cognition and decision making. Knowing the context is a key factor when robots must act in an embodied system. Purely functional representations may not be sufficient, requiring the enablement of context-aware decision-making in robotics. This requires updating the corrected behavioral schema to the robot. A last point is that the presence of robots causes changes in the behavior of humans. In this survey paper on Human Behavior in HRI, the goal is to illustrate the points of contact between robotics and human behavior. The approach for classifying recent papers in this study is based on two categories of human-centered human-robot interaction and robot-centered human-robot interaction. Here, we are presenting a unified review of HRI-related problems with a focus on human behavior modeling through identifying important themes, discussing the limitations of the existing methods, and suggesting potential directions for future research to find more interesting results this field.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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