International Journal of Social Robotics
https://doi.org/10.1007/s12369-022-00954-2

Human-Like Movements of Industrial Robots Positively Impact Observer Perception

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Accepted: 2 December 2022

Abstract

The number of industrial robots and collaborative robots on manufacturing shopfloors has been rapidly increasing over the past decades. However, research on industrial robot perception and attributions toward them is scarce as related work has predominantly explored the effect of robot appearance, movement patterns, or human-likeness of *humanoid* robots. The current research specifically examines attributions and perceptions of industrial robots—specifically, articulated collaborative robots—and how the type of movements of such robots impact human perception and preference. We developed and empirically tested a novel model of robot movement behavior and demonstrate how altering the movement behavior of a robotic arm leads to differing attributions of the robot's human-likeness. These findings have important implications for emerging research on the impact of robot movement on worker perception, preferences, and behavior in industrial settings.

Keywords HRI · Industrial robots · Articulated robot · Collaborative robots · Human-likeness · Anthropomorphism · Acceptance · Movements

1 Introduction

According to the International Federation of Robotics' (IFR) 2021 World Robot Report, the robot density in manufacturing nearly doubled from 66 robots per 10,000 employees in 2015 to 126 robots while the market grew by 12% for professional service robots and by 16% for consumer service robots in 2020 [1,2]. Since the number of robots is increasing in both private and business contexts, the design of more ergonomically and psychologically pleasing interactions between humans and robots is gaining increased importance. This is especially true for collaborative robots that are explicitly built for close (physical) collaboration with humans in the absence of classical protective equipment [3–7].

Existing research in the human–robot interaction (HRI) field focuses on the effects of appearance and behavior of *humanoid and service robots* that exhibit human-like characteristics such as gaze or voice [7,8]. However, given the increasing deployment of collaborative industrial robots on shopfloors, more research on the downstream effects on worker perception in industrial contexts is needed. With this study, we specifically examine the effects of different movement behaviors on the perception and attributions toward industrial collaborative robots.

In contrast to humanoid robots with their human-like characteristics, *articulated* robots have only limited human-like features and cannot interact through facial expression or voice cues. Industrial articulated robots are characterized by rotary joints and have limited degrees of freedom (DoF), depending on the number and arrangement of their joints. They are used for several applications on industrial shopfloors such as material handling, packaging, assembly, welding, or painting. Unlike conventional industrial robots, collaborative robots (cobots) do not require protective devices such as fences, as they have sensors that prevent injuries to their human co-workers. The objective of this paper is to provide a first systematic test of the movement patterns

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Published online: 20 December 2022

of such cobots impact the subjective perceptions of the human observer.

This paper is structured as follows. After a review of related work in the HRI field (Sect. 2), we outline the design and procedures of a causal experiment that isolates distinct movement behaviors of robotic arms and the effects of these distinct movement modalities on perceived human-likeness as well as preference (Sect. 3). We then present the empirical results in Sect. 4, a general discussion in Sect. 5, and discuss limitations in Sect. 5.1. Finally, we conclude and provide an outlook on future work in Sect. 5.2.

2 Related Work

Several studies have investigated the relationship between a robot's appearance, behavior, human-likeness, and effects of these dimensions on resulting interactions with humans. This line of research across technology, psychology, sociology, and economics investigates effects such as that humans communicate and observe their and others' internal states through *how* they perform certain actions or the influence of co-verbal gestures and eye gaze on interactions between humans and humanoid robots. The findings of this line of research includes, inter alia, that people tend to anthropomorphize robots that use co-verbal gestures more [9] and that human responses to robot vs. human gaze differs [10], even for infants, as demonstrated by Manzi et al. [11]. In order to influence the perception of industrial cobots by humans through a modulation of their movement behavior, a deeper understanding of how these movements are perceived by humans is required. Regarding planning of robot movements, several streams of research [6,12–14] focused on transparency perceptions, proposing strategies to improve the predictability and legibility of robot movements to enable more ergonomic robot–human interactions. Apart from effects on and perceptions of the individual, adjacent research fields investigated the acceptance of robots and automation in general on *actual* shopfloors and with *real workers*. Lotz et al. [5] found workers' concerns such as job loss and safety issues to be relevant to hinder acceptance, while enjoyment and output quality reinforced robot acceptance. For the present study, this indicates the potential to increase individuals' evaluation of industrial robots if movement behaviors are more intentionally designed and modulated in a way that reduce (at lest some of) these obstacles such as enhacing their perceived safety or enjoyment.

We survey the main relevant results from these fields along with a brief discussion of human-human interactions in the following section (Sect. 2.1), and discuss specifically the importance of human-likeness attributions. Subsequently, in Sect. 2.2 we discuss relevant key constructs, followed by a discussion of related studies that modulated robot behavior and serve as groundwork for the design of manipulations in our context (see Sect. 2.3).

2.1 Human-Likeness and the Anthropomorphization of Objects

Many research fields try to explain the human–machine relationship based on findings from studying interactions among people. Many of the identified mechanisms are applicable to robots as well and can be used to better design human–robot interactions. For example, *media equation theory* articulates that people tend to attribute human behavior and emotions to technical devices. Reeves and Nass [15] were able to show that people are not only polite to people but also to computers, and that *social* rules apply to inanimate media as well, even though the computer "showed plain text on a plain black-and-white screen" and did not have any artificial intelligence, virtual reality, or "any other obvious display of social presence" [15]. Interactions, i.e. "the capacity to react to what was and is being said and done" [16] therefore have the potential to be designed to have robots behave in more desirable ways when collaborating with humans. Anthropomorphism refers to people relating with non-human entities in similar ways as if these were humans and, with regard to humans, "involves the tendency to attribute human characteristics to robots" [17]. These effects exist with different objects and in different situations, e.g., even natural disasters or diseases may be "described in anthropomorphic terms" if an individual is personally affected [18]. Airenti discusses that "we may also anthropomorphize objects that we see as obstacles to our action, such as a door that does not open" and "we feel as an obstacle the fact that something that *should* cooperate with us actually does not". Since all objects that are able to cooperate with us or hinder our activities "may be the target of an anthropomorphic attitude" and since robots "are purposefully constructed to interact with humans", these effects are hypothesized to be even stronger when interacting with robots. In addition, such effects underlie individual and cultural differences: a lonely person without social contacts establishes more imaginary relations with non-human entities [18]. Moreover, these effects are also moderated by prior experiences: Mohammad and Nishida [19] demonstrates that only a few minutes of interaction with a robot can make a difference with regard to the effect on the assessment of the robot's human-likeness.

With regards to the attribution of human characteristics to robots, we need to understand the circumstances and features that result in the perception of human-likeness. The dimensions of "(de)humanization"—uniquely human characteristics (UH) and human nature (HN) [20]—can be used as guidance when attempting to humanize robots and their behavior. Considering that "UH imply higher cognition, civility, and refinement" whereas "HN involve emotionality, warmth, desire, and openness" [19], we focus on *lacking HN* which is referred to as *mechanistic dehumanization* and means that entities are considered "inert, cold, rigid, fungible and lacking agency" [20]. In a similar sense, "mind perception", based on Theory of Mind (ToM), refers to the question of who or what is perceived to have a mind [21]. Gray et al. [22] identified two factors when assessing the perception of different characters' minds (the characters were young children, animals, social robots, and God): *Experience* and *Agency*. Using these concepts, desired characteristics of a robot can be modulated, and it might be possible to improve the perceived human-likeness not only of social robots with humanoid features, but also of industrial articulated robot arms. Several studies demonstrated that perceived human-likeness has an influence on positive interactions: Koda and Maes [23] shows that an agent with a human-like face is considered more *likeable* and *engaging* than an agent without face. Powers and Kiesler [24] demonstrates how different face and verbal configurations (such as *male voice* or *short chin*) lead people to create certain mental models of the robot. Through these models, people then assess the "robot's credibility as an advisor" based on the consistency of the model's traits (e.g., matching of (male) voice and (long) chin) and their "similarity to people and machines, gender, and social and intellectual traits". Hinds et al. [25] compares human-like and machine-like robots and finds differences in people's intention to feel responsible for a task. Riek et al. [26] finds that people are more empathetic toward human-like robots, compared to mechanical-looking robots, further emphasizing our argument that the manipulation of robot *behavior* might be used to positively influence preferred outcome parameters.

A related area of research examining the impact of robot movements is the kinematics field and more specifically *how* certain actions (or movements) convey social signals to an interaction partner. These action dynamics—called 'vitality forms' by Stern [27] allow the sender to express their internal state as well as the receiver to understand other's internal states [28]. For example, the objective evaluation method of *Motor Inference* (MI) assesed how"face-to-face observation of a different (incongruent) movement of another individual leads to a higher variance in one's own movement trajectory". Given the lack of an anthropomorphic appearance, interactions with industrial robots are arguably less intuitive and, according to Kupferberg et al., motor inference may disappear when observing an industrial robot's piece-wise constant velocity [29]. However, humans are not only able to understand *what and why* of others' actions—i.e., the expressed goal-direction—, but also *how* these actions are performed—the vitality form [30]. It is therefore conceivable that individuals infer social signals from industrial robots even in the complete absence of any anthropomorphic cues.

To summarize, humans have a tendency to anthropomorphize robots and exhibit a general preference for more human-like robots. We therefore hypothesize that *human-like movements and behaviors of an industrial cobot may lead to more desirable interactions between robots and individuals*. We are specifically interested in examining this hypothesis in the context of industrial robots due to their complete lack of human-like characteristics.

2.2 Assessing Robot Perception and Human-Likeness

Several measurement scales to investigate the effect of robot behavior and characteristics, both qualitatively and quantitatively, have been proposed in the past. Bartneck et al. [31] presents a series of questionnaires—called *Godspeed*—to measure human perception of robots, using the constructs of *anthropomorphism*, *animacy*, *likeability*, *perceived intelligence*, and *perceived safety*. With regards to human-likeness and ToM, "the attribution of internal states to the robot, i.e., to have a mind, is widely used and very promising in HRI" [32]. An adjusted Attribution of Mental States (AMS) questionnaire was used in a study of Manzi et al. investigating the effect of different robot designs on children, consisting of the five dimensions: perceptive, emotive, desires and intentional, imaginative, and epistemic.

To align our experiment with the above-mentioned human preference for human-like robots, we use the Godspeed anthropomorphism scale to measure perceived human-likeness when interacting with a robot. The semantic differential can be used to measure whether a manipulation of robot behavior affected participant's perceptions of a robot and is further described in Sect. 3.4.

To inform the design of such manipulations, the following section reviews prior research that modulated the appearance, movements and behavior of (predominantly) *humanoid* robots.

2.3 Manipulation of Robot Appearance and Behavior

Investigations of the effects of robot characteristics on their interactions with humans also have a long record in HRI research and can be divided into several distinct fields. Robert et al. [33] assesses the current state of human–robot personality research in an extensive literature review that surveys 83 articles and 84 separate studies and summarizes key dimensions that were used to investigate the impact of robot personality: *Robot behavior* "was the most common independent variable used to invoke robot personality", including physical (gestures, movement patterns, facial expression and gaze) and communicative behavior (audio style, written text, linguistic style, voice gender voice speed and responsiveness) [33]. The *appearance of robots* "largely depended on the robot used" and included robots with faces—either physically simulated or displayed on a screen—and different physical sizes [33]. We attempt to transfer existing findings from humanoid robots to the expressive abilities of industrial robots, in line with Elprama et al. who mention "considering the expected growth of the cobot market, it is surprising how little research focuses on factory workers that are or will be working with these cobots and the impact on their working practices" [7] and Onnasch & Hildebrandt's statement that "research is needed to understand the effect of a robot's anthropomorphic features in work-related domains" [34]. The following paragraphs provide a succinct overview of existing research on the effect of different robot behaviors and appearances, with a focus on human-like design elements.

With regard to robot *appearance*, one of the earliest findings is the *Uncanny Valley* effect, i.e. the non-linear perception of robots with human-like appearance [35]. With regards to an industrial robot, it remains open if these findings can be replicated using an articulated robot arm. On the other hand, Marchetti et al. [36] discusses the relevance of artificial agents' anthropomorphic cues to recognize qualities such as mind, particularly face and gaze, and the positive effect on interactions with agents. However, our aim in the present study is to exclude human-like appearance features like adding a face to an industrial robot. For the sake of completeness, existing findings on the effect of such features will still be presented hereafter. More recent studies investigated effects of face displays on mind and personality perception [37] and found a preference for robots with a human-like face display versus silver-face or no-face on-screen displays. In addition, robots with a human-like face were rated as "having most mind, being most human-like, alive, sociable and amiable". With regards to human-like appearance, Phillips et al. [38] proposes a database (ABOT) that decomposes robots' human-like appearance and allows researchers to predict how human-like new robots will be perceived based on various appearance dimensions and features. Onnasch & Hildebrandt [34] investigated the impact of anthropomorphism on trust and visual attention allocation using an industrial cobot with a display that "showed an abstract face consisting of two eyes and according eyebrows" as a surrogate humanoidization mechanism. "In contrast to numerous positive results of anthropomorphic design in social HRI", they found no positive effects of anthropomorphism [34]. This result goes in line with our aim to only use a cobot's arm without any other human-like cues and to isolate the effect of movement behaviors exclusively.

On the other hand, the design and effect of robot *movements* evolved in various studies, including gesture expressivity for virtual agents [39] with the result that "identical gesture type may convey very different meanings depending on its quality" and for robot movements, Castro-Gonzalez et al. [40] demonstrates that naturalistic movement characteristics determine people's responses to a robot's likeability. Regarding the design of ergonomic hand-over tasks between robots and humans that result in safe, legible, and socially acceptable robot behavior [41–43], Mainprice et al. [41] finds three human constraints to be relevant to compute the most suitable place for an object transfer: *distance*, *visibility*, and *comfort*. Several studies investigated anthropomorphic industrial robot motions and their effects on transparency and human predictability [6,12–14] and demonstrated "shorter prediction time and fewer errors when using anthropomorphic speed profiles" [6]. Salem et al. [9] reports that specific *co-verbal* hand and arm gestures of humanoid robots have an effect on perceived anthropomorphism, likeability, shared reality and "increased future contact intentions than when the robot gave instructions without gestures". Bortot et al. [44] investigates predictability characteristics of robot movements and finds that variation in robot velocity has negative effects on human performance and well-being, and that constant, linear motion of the robot's end effector "seem[s] to be the most promising way to program the robot if you want to reach high levels of human well-being and performance" [44].

With regard to vitality forms, a kinematic study of Di Cesare et al. demonstrated a rude and a gentle vitality form in visual, auditory, and mixed modalities [28] where the visual stimuli were based on manipulating velocity and trajectory of actors' arms. Their results indicated that "the perception of vitality forms modulated the kinematic parameters (i.e., velocity and trajectory) of the subsequent actions performed by the participants". In contrast to constant velocity profiles, Kupferberg et al. used a "minimum-jerk" velocity profile that "starts slowly, accelerates smoothly to a peak velocity near the midpoint, and then decelerates slowly". Based on these designs, we therefore expect that manipulations of trajectories and velocity profiles have the potential to have important effects on human preference and will be revisited in the methods Sect. 3.

Regarding proximity to industrial robots and its effect on human acceptance, Eimontaite et al. [3] reports that working in close proximity to a robot increases mental workload and time pressure, but also satisfaction and perceived performance. We therefore include approach movements towards the participants, further explained in Sect. 3 as well. In addition, they found the *correspondence of task cycle times and robot task speed* to be a key design aspect for improved production quality and satisfaction. In their study evaluating a humanoid robot's human-likeness in shadowing tasks by Mohammad and Nishida [19], the relevance of taking different situations into account (simple shadowing vs. more complex imitation scenarios) was highlighted and demonstrated correlations between accuracy (imitative skills) and perceived human-likeness. In addition to studies focusing on either appearance or movements, some research focuses on combinations of both: Zlotowski et al. [45] reports on an experiment to research the effect of human-likeness of robot companions (manipulating appearance as well as behavior) and found “that a highly human-like robot is perceived as less trustworthy and empathetic than a more machine-like robot” whereas “negative behaviour of a machinelike robot reduces its trustworthiness and perceived empathy stronger than for highly humanlike robot[s]”. This seems to confirm to a certain extent findings from [34] as well as the Uncanny Valley. However, with regards to social cues of a collaborative robot in a pick-and-place task, Elprama et al. [7] shows that “the presence of more social cues increased perceived enjoyment and intention to work with cobots”. Comparing a robot with different levels of anthropomorphism and smooth vs. mechanistic movements, Castro-Gonzàlez et al. [40] found that “movement characteristics influenced the robot’s apparent animacy, likeability, and unpleasantness.” In addition, they found interdependencies between movements and appearance for animacy and unpleasantness.

Zanatto et al. [46] investigates how human-like social behavior of two robots affects perceived credibility of the robot, comparing more or less human-like conditions. Even though “people are more socially engaged with robots when they are more-humanlike”, they found that “if users were first primed with anthropomorphic robots they would be more accepting of their less-humanlike, but more functional, robotic relations”. Investigating the effect of social vs. economic function on mind perception, Wang and Krumhuber [47] found that robots with a social function “were perceived to possess greater ability for emotional experience” and demonstrated “a dissociation between function type (social vs. economic) and ascribed mind (emotion vs. cognition)”.

Further research investigates similar mechanisms, for instance that more anthropomorphic features resulted in more trust for autonomous vehicles to perform more competently [48] or increased satisfaction with UI designs that match the user’s personality type preferences [49]. Even though many studies focus on robot personality and human personality and how these explain robot perception [33,50–55], only few findings exist on moderating factors, i.e., relevant human characteristics explaining effects on varying robot acceptance. Regarding the influence of human and robot attributes for successful integration of social robots, Bishop et al. [56] reports that gender and education were not associated with acceptance, whereas age and mood correlated partly with the acceptance items used. In addition, results showed correlations for robot familiarity and displayed robot emotion with acceptance. With regard to gender differences in the perception of anthropomorphic and robotic movements, Abel et al. [57] finds that males were sensitive to the different manipulations of anthropomorphic and robotic movements while females were not; however, female participants in their study attributed more anthropomorphic features to robotic movements overall. To consider these findings, we also examine potential moderation effects related to demographic differences. Szczepanowski et al. [58] investigates the influence of education, attitudes toward, and familiarization with robots on social robot perception and reports relations; for instance, students with engineering education evaluated robots more favorably than students of psychology. Regarding the general use of robots, gender, age and urban/rural places of residence seem to play a role in shaping a person’s attitude towards robots [59–61].

In summary, the majority of these studies—motion-oriented, appearance-oriented, and combined—consider human-likeness to structure either the design of the interaction or to measure its outcome. Although some studies found contradicting effects, human-likeness seems to be valuable to understand how specific robot movements impact attributions of human-likeness. Since we test the ability of an articulated robot without any human-like cues except its arm to represent human-likeness, we expect that the uncanny valley effect examined in earlier work lacks face validity and relevance in the current work.

2.4 Hypotheses

As described and summarized in Sects. 2.1–2.3, we test several key hypotheses in the current research. The objective of this research is to test two key hypotheses that assess the extent to which movement patterns of industrial robots impact individual’s perception and subsequent preference. The focus of this research is to modulate the behavior of an articulated robotic arm without any human-type affordances such as face, mimic, or voice but with distinct movement abilities that are limited by the robot’s DoF.

Based on the cumulative evidence and research summarized earlier, we seek to test two key hypotheses:

- H1: The movement behavior of an articulated robot can be manipulated such that the perceived human-likeness of the robot increases.
- H2: Higher perceived human-likeness of robot movements leads to an increase in preference for that robot.

In the following, we discuss the stimuli and how we manipulate the robot’s specific pattern of movement.

3 Methods

In this study, we isolate the distinct effects of movements of industrial collaborative robots observed by humans, focusing

Table 1 Demographic summary of participants

Sample	Counts	Group			
Age, median age group = 30–39 years old					
Under 19	7	1			
20–29	33	2			
30–39	25	3			
40–49	14	4			
50–59	14	5			
60–69	7	6			
Gender					
Female	63				
Male	33				
Other	2				
Prefer not to answer	2				
Experience with	*Domestic robots*	*Military robots*	*Medical robots*	*Service robots*	*Industrial robots*
No	75	99	94	94	98
Yes	25	1	6	6	2
Location					
North America	18				
Europe	39				
Africa	32				
Australia	10				
Prefer not to answer	1				
Education					
5–12 years of schooling	3				
Some secondary school	1				
Senior secondary schooling	10				
Post-high school training	10				
Some college	20				
College graduate	54				
Prefer not to answer	1				
Total number of participants	**100**				

on perception of human-likeness and individual preferences. To test our hypotheses we have conducted a Web-based experiment using videos of actual industrial robots that perform specific movements, e.g., grabbing of an object. In Sect. 3.1 we describe our sample and in Sect. 3.2 we present the stimuli used in our experiment, i.e. how we manipulated the movement of an industrial collaborative robot. Section 3.3 explains the procedures and design of the study and finally, we report the key measures used in Sect. 3.4.

3.1 Participants

100 participants were recruited using *Prolific Academic* and were pre-screened for English being their first language. We used a within-subjects design to ensure greater statistical power and the final sample size was determined by apriori power calculations (G*Power 3.1) assuming intermediate effect sizes with repeated measures. Table 1 provides a detailed description of the sample.

3.2 Stimuli: Manipulation of Robot Movement

To design effective movement manipulations, existing findings and logical deduction from human-like movements were used to generate ideas and implemented within the limits of the robot's DoF. Kuz et al. [62] tested different speed profiles (anthropomorphic vs. constant). Castro-Gonàlez [40] tested mechanistic vs. smooth movement types, where in the mechanistic condition, "it executed a series of short, perpendicular movements" and in the smooth condition, "the arm followed a relatively efficient trajectory toward its goal–a shallow arc". Walther et al. [63] demonstrates how robots' approach directions were perceived, resulting in preferences for front-left and front-right approaches, whereas approaches

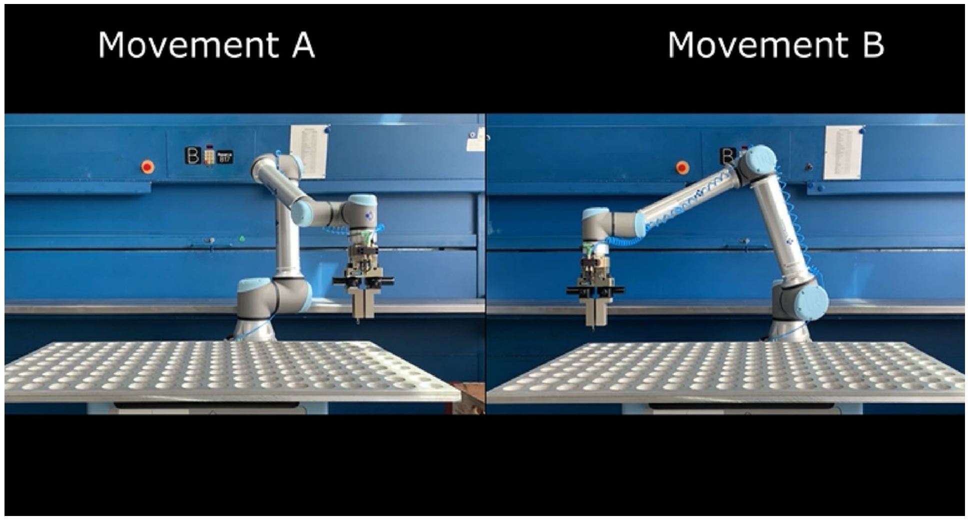

Fig. 1 Example frame of the generated video

from the rear were rated as being the least comfortable. In addition, personality research from adjacent research areas suggests that several gestures and features such as leaning backwards, turning away, frequency of body movements, narrow gesture amplitude, inward gesture direction, expansive/broad gestures and speed affect human perception [64–66]. Using these indications on how to design distinctive movement behaviors, we have conducted several iterations with expert HRI researchers and implementations using a Universal Robots UR10e's[1] six DoF. Based on these theory-driven and phenomenon-driven iterations along with the DoF of industrial robots, we focused on six separable, distinct movement parameters: *speed*, *part approach*, *smoothness*, *rotation*, *movement range*, and *approach direction*. Each of these parameters can be manipulated in isolation while all others can be held constant (avoiding potential confounds of movement patterns). This corresponds to the discussed concept of vitality forms, where only the *how* of the movement varies whereas the *what*—the trajectory—remains constant. We then modulated a robot to exhibit two highly discriminating conditions per parameter as follows (we provide the actual stimuli along with all scales used in this research in the corresponding OSF data respository):

- *Speed*: 40% vs. 100% of the robot's maximum speed and acceleration.
- *Part Approach*: Speed reduction before gripper opens, quick stop before lowering, lowering at reduced speed, lifting up at reduced speed vs. no stop and no speed reduction when gripping the part.
- *Smoothness*: Rounding of curves and steady movement vs. "connecting dots" with quick stops at 5 coordinates.
- *Rotation*: Three rotations vs. six rotations of the wrist joint, other joints rotating accordingly.
- *Movement Range*: 20% (of the robot's maximum) x-axis and z-axis movements (towards the camera and upward) vs. 80% x-axis and 50% z-axis movements.
- *Approach Direction*: Movement to the side and approach from the right vs. movement straight towards the camera/participant.

3.3 Design and Procedures

Using the described setup, we conducted a Web-based experiment with video stimuli of a UR10e robot due to the inability to conduct in-person lab studies during the COVID-19 pandemic.

The experimental setup was a within-subject design assigning the participants to all parameters and conditions with full randomization to counter order effects. We used a within-subjects design to ensure greater statistical power to detect the effect [67]. All participants were asked to watch the six videos of the robot and each video was split left/right according to condition A/B, playing consecutively. To avoid dependencies, the placement and order (left/right) of conditions was fully randomized. In addition, the order of the videos 1–6 as well as the order of the semantic differential scale's dimensions was fully randomized as well. The full questionnaire as well as the datasets generated during and analysed during the current study are available in the OSF data repository.[2]

To use these manipulations in Web-based experiments, videos of all movements were recorded resulting in two videos per parameter (conditions A and B) and the two recordings of each parameter were combined into six videos (see Fig. 1; see also OSF repository). We chose this experimental paradigm to allow a larger-sized sample and increase

[1] See https://www.universal-robots.com/products/ur10-robot/.

[2] See https://osf.io/qu4bv/?view_only=a1e79435c3194bcf834146350d97db5a.

Table 2 Stimuli, intuitively named for simpler referencing, no value statement intended

Parameter	Condition A	Condition B
Speed	Slow	Fast
Part approach	With care	Without care
Smoothness	Calm	Nervous
Rotation	Conventional rotations	Unconventional rotations
Movement range	Small movement range	Large movement range
Approach direction	From the side	Straight towards participant

statistical power of our findings. All recordings were conducted under tightly controlled settings (same recording angles, ecological industrial setting, etc.). Since people spontaneously make social inferences with others (and machines) not only "in face-to-face interactions, but also in technology-mediated settings—e.g., when observing people in a video" [51], we assume that the recognition of human-likeness of the robot's movements resembles an ecological test setting also when using videos as stimuli. Table 2 summarizes the parameters and conditions (condition labels in what follows were chosen only for exposition purposes).

3.4 Measures

To ensure that all manipulations work as intended, a *manipulation check* was conducted. Accordingly, we asked all participants about their general perception of the manipulation, detached from further questions regarding the perceived human-likeness. All participants were asked to rate the two conditions for all parameters in order to assess whether the manipulation works as intended (using a 5-point Likert scale). For instance, for the *speed* parameter: "Please indicate your perception of the robot's speed for movement A with the five response options *very slow*, *slow*, *neutral*, *fast*, *very fast*" (and similarly for movement condition B). Likewise, for the parameter *approach direction*, the question was "Please indicate your perception of approach A towards you" with the response options *from the side*, *a little from the side*, *neither from the side nor straight towards you*, *a little straight towards you* and *straight towards you*, and similarly for condition B as well as accordingly for all parameters.

The second block of questions investigating *perceived human-likeness* of the movement parameters consisted of a semantic differential scale, surveyed for both conditions A and B separately. The semantic differential scale assessed human-likeness based on the Godspeed Questionnaire (see Table 3) and participants were asked to rate each dimension on a 1–5 scale consisting of two opposite adjectives at each end of the scale. The last question investigated the participants' preference for one of the movement behaviors

Table 3 Semantic differential—human-likeness

Fake	1	2	3	4	5	Natural
Machinelike	1	2	3	4	5	Humanlike
Unconscious	1	2	3	4	5	Conscious
Artificial	1	2	3	4	5	Lifelike
Moving rigidly	1	2	3	4	5	Moving elegantly

(A/B) for each parameter with the question "Which movement behavior do you prefer?".

In addition to the participants' evaluation of the robot movements, demographic data (age, gender, location, education) as well as prior experience of the participants with robots (across the robot categories *domestic*, *military*, *medical*, *service*, and *industrial*) was recorded to check for potentially moderating effects.

3.5 Data Analysis Procedures

Rating scores were analyzed using repeated measures ANOVAs to assess the main effects of robot movements. In addition, we checked for interactions between movement parameters (Speed, Part Approach, etc.), conditions (A/B), and questionnaire items (manipulation check & human-likeness items). Finally, we further assessed potential three-way interactions and whether the condition effects were moderated by demographic characteristics (see Tables 7, 8, 9, 10, 11 and 12 in the appendix for additional statistical results). Due to the slightly unequal gender distribution and prior knowledge differences, we also carried out several additional robustness checks on specific sub-samples of the data. Greenhouse–Geisser correction was used if the sphericity assumption was violated. We report LSD corrections for multiple comparisons, only running pairwise comparisons in case of a significant higher-order interaction effects. The dataset contained no influential outliers as the value range for all human-likeness items was inside the 3rd quartile + 3*interquartile range and the 1st quartile − 3*interquartile range (visually gleaned via a series of Boxplots).

Table 4 Two-way interactions between conditions and questionnaire items per movement parameter

Repeated measures ANOVA	Results
2 (Conditions) × 6 (Speed)	$F(5, 495) = 74.711,\ p < 0.001,\ \eta p^2 = 0.430$
2 (Conditions) × 6 (Part approach)	$F(5, 495) = 26.649,\ p < 0.001,\ \eta p^2 = 0.212$
2 (Conditions) × 6 (Smoothness)	$F(5, 495) = 153.446,\ p < 0.001,\ \eta p^2 = 0.608$
2 (Conditions) × 6 (Rotation)	$F(5, 495) = 23.515,\ p < 0.001,\ \eta p^2 = 0.192$
2 (Conditions) × 6 (Movement range)	$F(5, 495) = 32.689,\ p < 0.001,\ \eta p^2 = 0.248$
2 (Conditions) × 6 (ApproachDirection)	$F(5, 495) = 79.096,\ p < 0.001,\ \eta p^2 = 0.444$

4 Results

The rating scores were analyzed using 2 (conditions) × 6 (questionnaire items) repeated measures ANOVAs, separately for each movement parameter. The first pair of the six questionnaire items represented the manipulation check items, whereas the other 5 pairs represented the human-likeness scale. The analysis demonstrates that there were significant two-way-interactions between conditions A/B and the questionnaire items for each of the movement parameters (with all $p < 0.001$, see Table 4).

Since all interactions reached significance, we further assessed multiple pairwise comparisons of the two conditions across the six items, separately for each movement parameter. For each movement parameter's questionnaire items, paired sample t-tests were performed. Consistent with the presented interactions, participants perceived the two conditions significantly different for all manipulation checks across all movement parameters with all $p < 0.001$. The depicted Partial eta-squared (ηp^2) represents the strength of the respective effect.

With regard to perceived human-likeness, measured using the semantic differential scale, three parameters reached statistical significance when comparing the per-item means of Condition A vs. Condition B across all participants: *Speed*, *Smoothness*, and *Rotation*, see Figs. 2 and 3 on the next pages. Detailed statistics can be found in the appendix in Tables 13, 14, 15, 16, 17 and 18. The results of the critical tests remain significant also after using a more conservative Holm–Bonferroni correction for multiple comparisons. We also performed further robustness checks and assessed potential demographic and prior experience moderation effects, which led to robustness of results and no consistent boundary conditions across age groups or conditional on prior experience (see Tables 7, 8, 9, 10, 11 and 12 in the Appendix). Regarding the parameters *Part Approach*, *Movement Range*, and *Approach Direction*, only some of the semantic differential outcomes were perceived significantly more/less human-like,even though movement range reached an overall significant effect for 4 out of 5 Godspeed-items.

To assess whether preference was greater for condition A or B, we performed additional Chi-Square tests for the participant preference data across all movement parameters. In line with the preceding results, we observed significant differences in choice shares for the same three movement parameters that were perceived as more human-like: *Speed*, *Smoothness*, and *Rotation*. The conditions for the other three movement parameters were not significantly different (see Table 5).

To confirm the correlations between human-likeness ratings and preference choices (as hypothesized in *H2*), point biserial correlations were calculated. We did this by summing up the differences of the human-likeness items scores for each movement parameter and comparing them to the preference choices per movement parameter (A/B). Thus, difference scores were summed over all items to create a composite score of human-likeness. These analyses revealed positive correlations for all movement parameters with all $p < 0.001$, demonstrating medium to high correlations of all preference choices and perceived human-likeness (see Table 6).

5 General Discussion

The results presented in the previous section show that three of the six movement parameters that we investigated were perceived significantly different in terms of human-likeness. Based on the participants' evaluations, human-likeness can be increased by having the robot:

- move slower (at 40% speed, compared to 100% speed),
- employ smooth, round curves (compared to more rigid, "nervous", movement patterns), and
- rotate conventionally (compared to additional, unnecessary rotations).

Referring to our hypotheses in Sect. 2.4, we can summarize that an articulated robot's movement behavior can be manipulated in order to increase perceived human-likeness of industrial robots: Even though the robotic arm has no face, voice or other human characteristics, the perceived human-likeness of the articulated robot arm increased significantly,

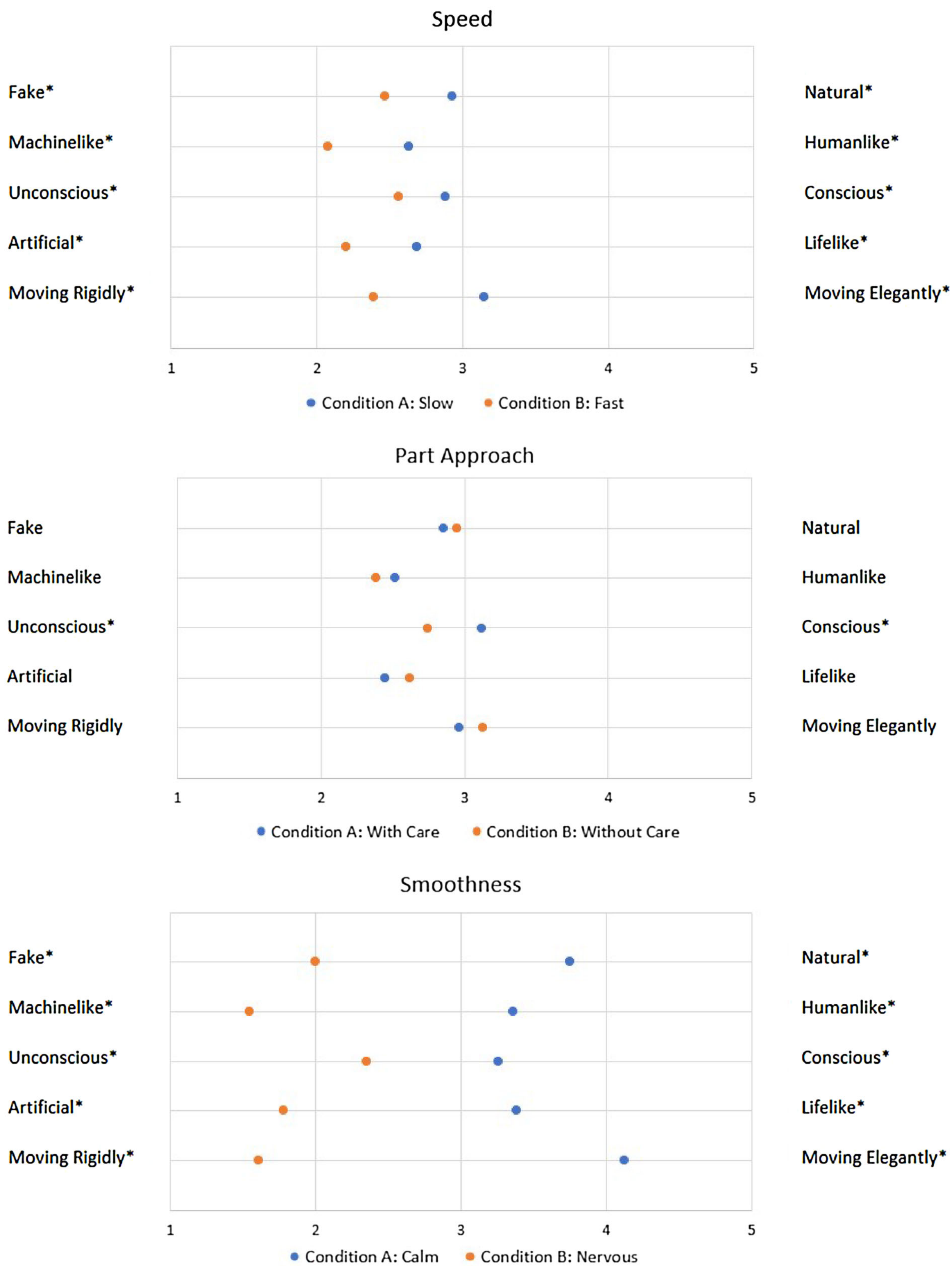

Fig. 2 Semantic differential: perceived human-likeness; asterisk (*) indicates statistical significant group differences at the $p < 0.05$ significance level

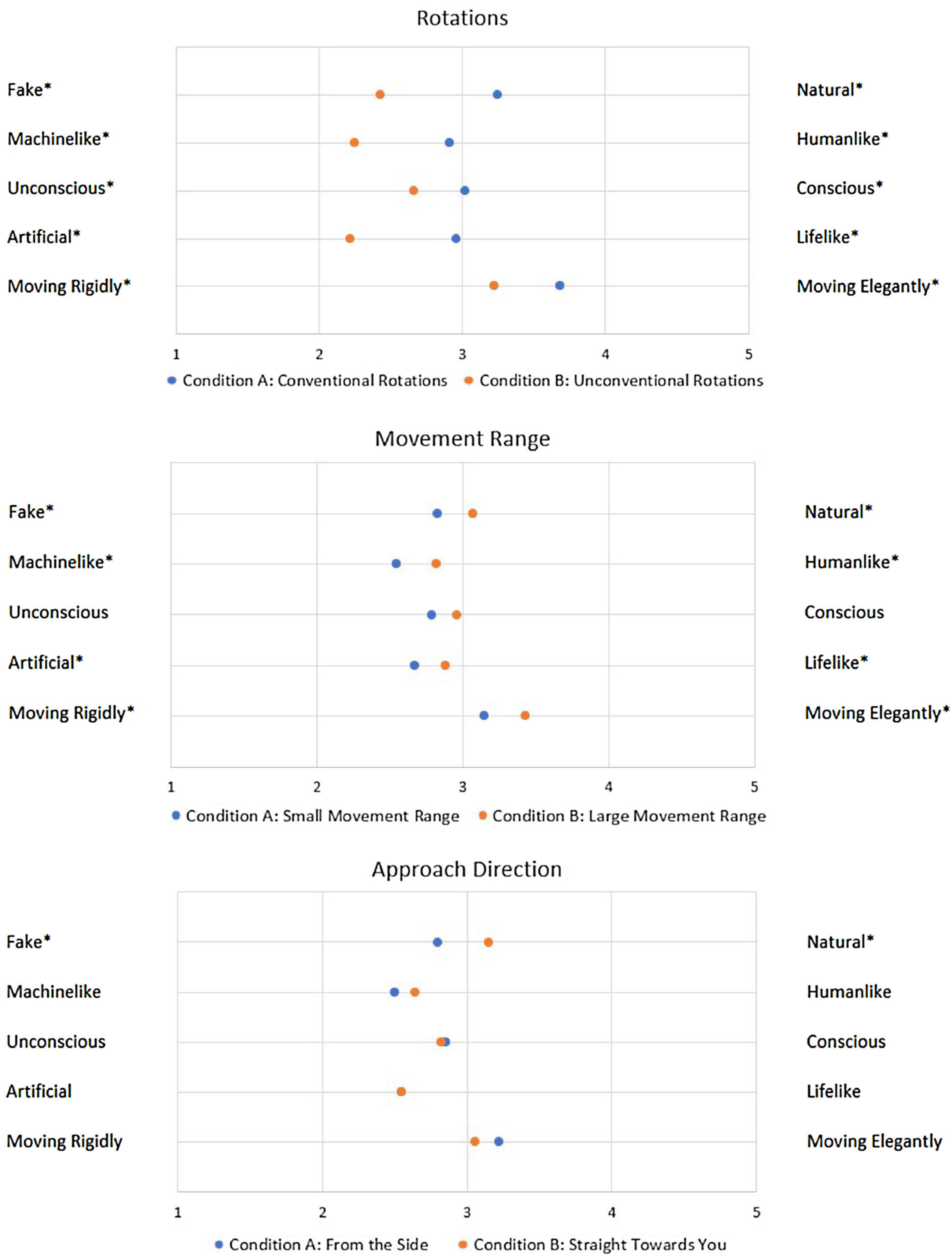

Fig. 3 Semantic differential: perceived human-likeness; asterisk (*) indicates statistical significant group differences at the $p < 0.05$ significance level

Table 5 Chi square tests

	Preferences	
	Chi-square	Asymp. Sig.
Speed	6.76	0.009
Part approach	1.44	0.23
Smoothness	60.84	< 0.001
Rotation	11.56	< 0.001
Movement range	0.16	0.689
Approach direction	0.36	0.549

Table 6 Point Biserial Correlations Between Movement Dimensions and Preference

	Correlations	
	Spearman's ρ	Sig (2-tailed)
Speed	0.367	< 0.001
Part approach	0.541	< 0.001
Smoothness	0.361	< 0.001
Rotation	0.452	< 0.001
Movement range	0.462	< 0.001
Approach direction	0.485	< 0.001

solely by manipulating well-defined dimensions of a robot's movement behavior.

In terms of theory (see Sect. 2.1), we thus showed that the mechanism of people attributing higher human-likeness unfolds for industrial robots as well. *H1 can therefore be accepted* for the movement parameters (lower) *Speed*, (higher) *Smoothness*, and (more conventional) *Rotation*. This contributes to several seminal theories outlined in Sect. 2.1 and sheds light on the ability of an industrial robot to be attributed human characteristics through distinct movement behaviors. In view of HN [20] it can even be assumed that the applied movement behaviors enable industrial robots to address mechanistic dehumanization and serve as framework to let them avoid being perceived as "inert, cold, rigid, fungible and lacking agency". Also, the current results are also consistent with prior work on vitality forms, as different levels of human-likeness of the robot's behavior were perceived even though the functional movement remained similar. With regards to behaviors and movements such as gestures, ergonomic trajectories, and eye contact, the majority of existing studies found human-likeness to be relevant for positive evaluations of HRI. However, some studies indicate deviating results [34,37], and the uncanny valley might be a relevant issue in industrial HRI as well. Relating to our study, the relevance of human-likeness can partially be confirmed by our results, even though not all movement parameters reached statistical significance, e.g., manipulated approach directions had no effect on perceived human-likeness in our study, differing from Bortot et al.'s findings [44].

Moreover, our results do support the positive effect of human-likeness on human perception. As demonstrated for the appearance of several humanoid robots, the preference for human-likeness when interacting with robots was examined by asking for participants' preferences, even though our UR10e robot had no human-like features (except its robotic arm). As expected, we found that observer preference and human-likeness were significantly correlated. The results show that for those three parameters that were perceived as more human-like, participants indicated a strong preference for those movement patterns, thereby *confirming H2*.

5.1 Limitations

As with any study, also the current study is not without limitations. Due to COVID-19 restrictions, we were only able to run web-based experiments and had to video-tape our industrial robot implementation. We expect that this less involving study setting led to somewhat more conservative results and that in-person experiments and direct interactions with industrial robots should result in stronger effects and permit to generalize our findings in the future.

To generalize our results, investigations of different robot tasks and applications, different industrial robot types, additional movement parameters and dependent variables as well as different demographic and cultural samples are required. In addition, as for most HRI studies [68] our study addresses the topic from a robot-related point of view whereas Weiss et al. [69] mentions human-related and contextual factors to be relevant to enable human trust in robots. It is therefore crucial to take into account individual differences as well as specific tasks in future industrial HRI studies. Future work may also employ higher powered samples. We also acknowledge that the sample in the current research was demographically unbalanced (underrepresentation of male participants and 98% of our study participants had not had any prior interactions with industrial robots, etc.). Although men represent the majority of manufacturing employees, gender-specific results might help the manufacturing industry to address women, being "the largest pool of untapped talent" [70]. Thus, despite the unbalanced sample characteristics, the current findings do have merit to inform future HRI research on industrial robots and potential gender moderation effects.

Future work may also expand the range of outcomes and processes that are examined. Given the wide range of technology acceptance frameworks and measures, future work may further assess variation as a function of the type of measurement. The technology acceptance framework for example has led to a varity of conceptual lenses and measurements, such as the *United Theory of Acceptance and Use of Technology* (UTAUT) as a further development of the *Technology*

Acceptance Model (TAM) [71]. Heerink et al. [72] further adapts and extends UTAUT to test the acceptance of assistive social agents by elderly users, establishing the ALMERE model. Focusing on HRI, the USUS evaluation framework addresses usability (U), social acceptance (S), user experience (U) and societal impact (S) of humanoid robots [73]. We propose that future research can likely benefit from linking our results on movement manipulations to these validated concepts of acceptance.

We also acknowledge that the current research was conducted with one specific type of robot (UR 10e). Future work may therefore model movement behaviors across a broader range of implementation settings on industrial shopfloors.

5.2 Conclusions and Future Research

The current experiment—to the best of our knowledge—is one of the first systematic assessments to investigate the relationship between movement behavior of industrial robots, perceived human-likeness and human preference. This research sheds light on how to modulate movement behaviors of a robotic arm in order to increase perceived human-likeness based on six distinct movement parameters. Although not all movement parameters were perceived significantly different, the findings support the hypothesis that specific movement behaviors of an industrial robot significantly influence perceived human-likeness and that human-likeness has a systematic effect on subsequent preferences for that robot. Three out of six parameters were found to have a significant influence on perceived human-likeness: Speed, Smoothness, and Rotation.

From a practical viewpoint, since the purpose of industrial robots is typically to contribute to increasing productivity, a reduction of *speed* might be contrary to this objective (even for collaborative robots). On the other hand, *smoothness*, i.e. the rounding of movement curves, does not affect the robot's productivity, and omitting unnecessary *rotations* supports the economic application of the robot. This emphasizes the need for further investigations of the effect of human-likeness for specific tasks.

Summarizing, our results demonstrate promising effects that can help to adapt robot movements to human preferences and future work may further explore whether these changes in preference subsequently enhance actual acceptance of industrial articulated robots. Enriching the existing findings with additional movement behaviors and including differentiating human characteristics would then promote the idea of devices that are able to adapt autonomously and in real time to relevant individual differences, and might in turn even increase individual user and worker acceptance. Such future work may also further explore the robustness of these effects across cultures and study actual worker responses in industrial shopfloor settings. We hope that our findings provide a fruitful foundation for future work examining both industrial robot settings as well as the critical role of robot movements on the attribution of human-likeness and on acceptance moving forward.

Funding The authors did not receive support from any organization for the submitted work. The authors have no relevant financial or non-financial interests to disclose.

Data availability The data and stimuli of this study are available in a public OSF data repository, https://osf.io/qu4bv/?view_only=a1e79435c3194bcf834146350d97db5a.

Declarations

Ethical Approval The Ethics Committee of the University of St. Gallen has confirmed that no ethical approval is required.

Appendix

Repeated Measures ANOVAs

See Tables 7, 8, 9, 10, 11 and 12.

Table 7 Repeated measures ANOVAs for movement parameter *speed*

Repeated measures ANOVA	Results
2 (Conditions) × 6 (Speed)	$F(5, 495) = 74.711$, $p < 0.001$, $\eta p2 = .430$
2 (Conditions) × 6 (Speed) × 6(Age)	$F(25, 470) = 1.100$, $p = 0.338$, $\eta p2 = 0.055$
2 (Conditions) × 6 (Speed) × 4 (Gender)	$F(15, 480) = .265$, $p = 0.998$, $\eta p2 = 0.008$
2 (Conditions) × 6 (Speed) × 2 (domestic robots)	$F(5, 490) = 1.113$, $p = 0.352$, $\eta p^2 = 0.011$
2 (Conditions) × 6 (Speed) × 2 (Military robots)	$F(5, 490) = 0.532$, $p = 0.752$, $\eta p2 = 0.005$
2 (Conditions) × 6 (Speed) × 2 (Medical robots)	$F(5, 490) = 2.337$, $p = 0.041$, $\eta p2 = 0.023$
2 (Conditions) × 6 (Speed) × 2 (Service robots)	$F(5, 490) = 0.678$, $p = 0.640$, $\eta p2 = 0.007$
2 (Conditions) × 6 (Speed) × 2 (Industrial robots)	$F(5, 490) = 0.056$, $p = 0.998$, $\eta p2 = 0.001$
2 (Conditions) × 6 (Speed) × 5 (Location)	$F(20, 475) = 0.501$, $p = 0.966$, $\eta p2 = 0.021$
2 (Conditions) × 6 (Speed) × 7 (Education)	$F(35, 460) = 1.271$, $p = 0.142$, $\eta p2 = 0.088$

Table 8 Repeated measures ANOVAs for movement parameter *part approach*

Repeated measures ANOVA	Results
2 (Conditions) × 6 (PartAppr.)	$F(5, 495) = 26.649$, $p < 0.001$, $\eta p2 = 0.212$
2 (Conditions) × 6 (PartAppr.) × 6 (Age)	$F(25, 470) = 1.758$, $p = 0.014$, $\eta p2 = 0.086$
2 (Conditions) × 6 (PartAppr.) × 4 (Gender)	$F(15, 480) = 1.465$, $p = 0.114$, $\eta p2 = 0.044$
2 (Conditions) × 6 (PartAppr.) × 2 (Domestic robots)	$F(5, 490) = .709$, $p = 0.617$, $\eta p2 = 0.007$
2 (Conditions) × 6 (PartAppr.) × 2 (Military robots)	$F(5, 490) = 0.964$, $p = 0.439$, $\eta p2 = 0.010$
2 (Conditions) × 6 (PartAppr.) × 2 (Medical robots)	$F(5, 490) = .442$, $p = 0.819$, $\eta p2 = 0.004$
2 (Conditions) × 6 (PartAppr.) × 2 (Service robots)	$F(5, 490) = 0.472$, $p = 0.797$, $\eta p2 = 0.005$
2 (Conditions) × 6 (PartAppr.) × 2 (Industrial robots)	$F(5, 490) = 0.355$, $p = 0.879$, $\eta p2 = .004$
2 (Conditions) × 6 (PartAppr.) × 5 (Location)	$F(20, 475) = 0.748$, $p = 0.776$, $\eta p2 = 0.031$
2 (Conditions) × 6 (PartAppr.) × 7 (Education)	$F(35, 460) = 2.081$, $p < 0.001$, $\eta p2 = 0.057$

Table 9 Repeated measures ANOVAs for movement parameter *smoothness*

Repeated measures ANOVA	Results
2 (Conditions) × 6 (Smoooth)	$F(5, 495) = 153.446$, $p < 0.001$, $\eta p2 = 0.608$
2 (Conditions) x 6 (Smoooth) × 6 (Age)	$F(25, 470) = 1.352$, $p = 0.121$, $\eta p2 = 0.067$
2 (Conditions) × 6 (Smoooth) × 4 (Gender)	$F(15, 480) = 1.326$, $p = 0.182$, $\eta p2 = 0.040$
2 (Conditions) × 6 (Smoooth) × 2 (Domestic robots)	$F(5, 490) = 0.432$, $p = 0.826$, $\eta p2 = 0.004$
2 (Conditions) × 6 (Smoooth) × 2 (Military robots)	$F(5, 490) = 0.290$, $p = 0.918$, $\eta p2 = 0.003$
2 (Conditions) × 6 (Smoooth) × 2 (Medical robots)	$F(5, 490) = .267$, $p = 0.931$, $\eta p2 = 0.003$
2 (Conditions) × 6 (Smoooth) × 2 (Service robots)	$F(5, 490) = .272$, $p = 0.929$, $\eta p2 = 0.003$
2 (Conditions) × 6 (Smoooth) × 2 (Industrial robots)	$F(5, 490) = 0.748$, $p = 0.588$, $\eta p2 = 0.008$
2 (Conditions) × 6 (Smoooth) × 5 (Location)	$F(20, 475) = 0.438$, $p = 0.985$, $\eta p2 = 0.018$
2 (Conditions) × 6 (Smoooth) × 7 (Education)	$F(35, 460) = 0.793$, $p = 0.797$, $\eta p2 = 0.057$

Table 10 Repeated measures ANOVAs for movement parameter *rotation*

Repeated measures ANOVA	Results
2 (Conditions) × 6 (Rotation)	$F(5, 495) = 23.515$, $p < 0.001$, $\eta p2 = 0.192$
2 (Conditions) × 6 (Rotation) × 6 (Age)	$F(25, 470) = 0.678$, $p = 0.879$, $\eta p2 = 0.035$
2 (Conditions) × 6 (Rotation) × 4 (Gender)	$F(15, 480) = 0.886$, $p = 0.580$, $\eta p2 = 0.027$
2 (Conditions) × 6 (Rotation) × 2 (Domestic robots)	$F(5, 490) = 0.225$, $p = 0.952$, $\eta p2 = 0.002$
2 (Conditions) × 6 (Rotation) × 2 (Military robots)	$F(5, 490) = 1.625$, $p = 0.145$, $\eta p2 = 0.017$
2 (Conditions) × 6 (Rotation) × 2 (Medical robots)	$F(5, 490) = 1.727$, $p = 0.127$, $\eta p2 = 0.017$
2 (Conditions) × 6 (Rotation) × 2 (Service robots)	$F(5, 490) = 1.071$, $p = 0.376$, $\eta p2 = 0.011$
2 (Conditions) × 6 (Rotation) × 2 (Industrial robots)	$F(5, 490) = 1.715$, $p = 0.130$, $\eta p2 = 0.017$
2 (Conditions) × 6 (Rotation) × 5 (Location)	$F(20, 475) = 0.641$, $p = 0.882$, $\eta p2 = 0.026$
2 (Conditions) × 6 (Rotation) × 7 (Education)	$F(35, 460) = 0.870$, $p = 0.684$, $\eta p2 = 0.062$

Table 11 Repeated measures ANOVAs for movement parameter *movement range*

Repeated measures ANOVA	Results
2 (Conditions) × 6 (Mov.Range)	$F(5, 495) = 32.689$, $p < 0.001$, $\eta p2 = 0.248$
2 (Conditions) × 6 (Mov.Range) × 6 (Age)	$F(25, 470) = 0.629$, $p = 0.919$, $\eta p2 = 0.188$
2 (Conditions) × 6 (Mov.Range) × 4 (Gender)	$F(15, 480) = 0.554$, $p = 0.909$, $\eta p2 = 0.054$
2 (Conditions) × 6 (Mov.Range) × 2 (Domestic robots)	$F(5, 490) = 0.621$, $p = 0.684$, $\eta p2 = 0.006$
2 (Conditions) × 6 (Mov.Range) × 2 (Military robots)	$F(5, 490) = 0.717$, $p = 0.611$, $\eta p2 = 0.007$
2 (Conditions) × 6 (Mov.Range) × 2 (Medical robots)	$F(5, 490) = 0.667$, $p = 0.648$, $\eta p2 = 0.007$
2 (Conditions) × 6 (Mov.Range) × 2 (Service robots)	$F(5, 490) = 0.727$, $p = 0.603$, $\eta p2 = 0.007$
2 (Conditions) × 6 (Mov.Range) × 2 (Industrial robots)	$F(5, 490) = 0.928$, $p = 0.462$, $\eta p2 = 0.009$
2 (Conditions) × 6 (Mov.Range) × 5 (Location)	$F(20, 475) = 0.786$, $p = 0.732$, $\eta p2 = 0.032$
2 (Conditions) × 6 (Mov.Range) × 7 (Education)	$F(35, 460) = 1.324$, $p = 0.106$, $\eta p2 = 0.092$

Table 12 Repeated measures ANOVAs for movement parameter *approach direction*

Repeated measures ANOVA	Results
2 (Conditions) × 6 (Appr.Dir.)	$F(5, 495) = 79.096$, $p < 0.001$, $\eta p2 = 0.444$
2 (Conditions) × 6 (Appr.Dir.) × 6 (Age)	$F(25, 470) = 1.213$, $p = 0.220$, $\eta p2 = .061$
2 (Conditions) × 6 (Appr.Dir.) × 4 (Gender)	$F(15, 480) = 0.882$, $p = 0.585$, $\eta p2 = 0.027$
2 (Conditions) × 6 (Appr.Dir.) × 2 (Domestic robots)	$F(5, 490) = 0.358$, $p = 0.877$, $\eta p2 = 0.004$
2 (Conditions) × 6 (Appr.Dir.) × 2 (Military robots)	$F(5, 490) = 0.383$, $p = 0.860$, $\eta p2 = 0.004$
2 (Conditions) × 6 (Appr.Dir.) × 2 (Medical robots)	$F(5, 490) = 0.270$, $p = 0.929$, $\eta p2 = 0.003$
2 (Conditions) × 6 (Appr.Dir.) × 2 (Service robots)	$F(5, 490) = 0.271$, $p = 0.929$, $\eta p2 = 0.003$
2 (Conditions) × 6 (Appr.Dir.) × 2 (Industrial robots)	$F(5, 490) = 0.422$, $p = 0.833$, $\eta p2 = 0.004$
2 (Conditions) × 6 (Appr.Dir.) × 5 (Location)	$F(20, 475) = 2.194$, $p = 0.002$, $\eta p2 = 0.085$
2 (Conditions) × 6 (Appr.Dir.) × 7 (Education)	$F(35, 460) = 0.866$, $p = 0.690$, $\eta p2 = 0.062$

Paired Samples T-Tests

See Tables 13, 14, 15, 16, 17 and 18.

Table 13 Paired samples T-tests for movement parameter *speed*

Speed	Paired differences								
	Mean[a]	Std. Dev.	Std. Error Mean	95% CI of Δ		t	df	Significance	
				Lower	Upper			One-sided p	Two-sided p
Manipulation check	– 1.660	0.927	0.093	– 1.843	– 1.476	– 17.908	99	< 0.001	< 0.001
Fake–natural	0.457	1.337	0.134	0.192	0.723	3.421	99	0.000	0.001
Machinelike–humanlike	0.550	1.507	0.151	0.251	0.849	3.650	99	0.000	0.000
Unconscious–conscious	0.321	1.418	0.142	0.040	0.603	2.267	99	0.013	0.026
Artificial–lifelike	0.490	1.411	0.141	0.210	0.770	3.474	99	0.000	0.001
Moving rigidly–moving elegantly	0.760	1.793	0.179	0.404	1.116	4.239	99	0.000	0.000

Table 14 Paired samples T-tests for movement parameter *part approach*

Part approach	Paired differences								
	Mean[a]	Std. Dev.	Std. Error Mean	95% CI of Δ		t	df	Significance	
				Lower	Upper			One-sided p	Two-sided p
Manipulation check	– 1.343	0.828	0.083	– 1.507	– 1.178	– 16.214	99	< 0.001	< 0.001
Fake–natural	– 0.095	1.361	0.136	– 0.365	0.175	– 0.700	99	0.243	0.485
Machinelike–humanlike	0.140	1.712	0.171	– 0.200	0.480	0.818	99	0.208	0.415
Unconscious–conscious	0.380	1.448	0.145	0.093	0.667	2.624	99	0.005	0.010
Artificial–lifelike	– 0.170	1.729	0.173	– 0.513	0.173	– 0.983	99	0.164	0.328
Moving rigidly–moving elegantly	– 0.170	2.015	0.202	– 0.570	0.230	– 0.844	99	0.200	0.401

Table 15 Paired samples T-tests for movement parameter *smoothness*

Smoothness	Paired differences								
	Mean[a]	Std. Dev.	Std. Error Mean	95% CI of Δ		t	df	Significance	
				Lower	Upper			One-sided p	Two-sided p
Manipulation check	– 2.034	1.205	0.120	– 2.273	– 1.795	– 16.881	99	< 0.001	< 0.001
Fake–natural	1.754	1.453	0.145	1.466	2.042	12.068	99	0.000	0.000
Machinelike–humanlike	1.810	1.509	0.151	1.511	2.109	11.996	99	0.000	0.000
Unconscious–conscious	0.910	1.634	0.163	0.586	1.234	5.571	99	0.000	0.000
Artificial–lifelike	1.600	1.435	0.144	1.315	1.885	11.146	99	0.000	0.000
Moving rigidly–moving elegantly	2.520	1.642	0.164	2.194	2.846	15.346	99	0.000	0.000

Table 16 Paired samples T-tests for movement parameter *rotation*

Rotation	Paired differences								
	Mean[a]	Std. Dev.	Std. Error Mean	95% CI of Δ		t	df	Significance	
				Lower	Upper			One-sided p	Two-sided p
Manipulation check	1.558	1.191	0.119	1.321	1.794	13.077	99	< 0.001	< 0.001
Fake–natural	0.824	1.179	0.118	0.590	1.058	6.986	99	0.000	0.000
Machinelike–humanlike	0.660	1.281	0.128	0.406	0.914	5.152	99	0.000	0.000
Unconscious–conscious	0.360	1.150	0.115	0.132	0.588	3.129	99	0.001	0.002
Artificial–lifelike	0.742	1.216	0.122	0.501	0.984	6.103	99	0.000	0.000
Moving rigidly–moving elegantly	0.460	1.438	0.144	0.175	0.745	3.198	99	0.001	0.002

Table 17 Paired samples T-tests for movement parameter *movement range*

Movement range	Paired differences							Significance	
	Mean[a]	Std. Dev.	Std. Error Mean	95% CI of Δ		t	df		
				Lower	Upper			One-sided p	Two-sided p
Manipulation check	− 1.393	1.190	0.119	− 1.629	− 1.157	− 11.713	99	< 0.001	< 0.001
Fake–natural	− 0.240	1.129	0.113	− 0.464	− 0.016	− 2.125	99	0.018	0.036
Machinelike–humanlike	− 0.280	1.045	0.105	− 0.487	− 0.073	− 2.679	99	0.004	0.009
Unconscious–conscious	− 0.174	0.948	0.095	− 0.362	0.014	− 1.835	99	0.035	0.069
Artificial–lifelike	− 0.209	0.998	0.100	− 0.407	− 0.011	− 2.091	99	0.020	0.039
Moving rigidly–moving elegantly	− 0.280	1.256	0.126	− 0.529	− 0.031	− 2.229	99	0.014	0.028

Table 18 Paired samples T-tests for movement parameter *approach direction*

Approach direction	Paired differences							Significance	
	Mean[a]	Std. Dev.	Std. Error Mean	95% CI of Δ		t	df		
				Lower	Upper			One-sided p	Two-sided p
Manipulation check	− 2.784	1.151	0.115	− 3.013	− 2.556	− 24.191	99	< 0.001	< 0.001
Fake–natural	− 0.350	1.629	0.163	− 0.673	− 0.027	− 2.148	99	0.017	0.034
Machinelike–humanlike	− 0.140	1.752	0.175	− 0.488	0.208	− 0.799	99	0.213	0.426
Unconscious–conscious	0.030	1.642	0.164	− 0.296	0.356	0.183	99	0.428	0.855
Artificial–lifelike	− 0.002	1.781	0.178	− 0.356	0.351	− 0.012	99	0.495	0.990
Moving rigidly–moving elegantly	0.160	1.968	0.197	− 0.230	0.550	0.813	99	0.209	0.418

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