Body Movement Mirroring and Synchrony in Human–Robot Interaction

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This review article provides an overview of papers that have studied body movement mirroring and synchrony within the field of human-robot interaction. The papers included in this review cover system studies, which focus on evaluating the technical aspects of mirroring and synchrony robotic systems, and user studies, which focus on measuring particular interaction outcomes or attitudes towards robots expressing mirroring and synchrony behaviors. We review the papers in terms of the employed robotic platforms and the focus on parts of the body, the techniques used to sense and react to human motion, the evaluation methods, the intended applications of the human-robot interaction systems and the scenarios utilized in user studies. Finally, challenges and possible future directions are considered and discussed.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Computer systems organization** → **Robotics**; • **Human-centered computing** → *Field studies*; *User studies*; *Collaborative interaction*; • **Computing methodologies** → Robotic planning; Cognitive robotics;

Additional Key Words and Phrases: human-robot interaction, body movement, mirroring, mimicry, synchrony

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1 Introduction

With the growing availability of social robots, interaction dynamics is becoming a topic of increasing interest, making the social interaction between humans and robots a research topic of high

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relevance. One of the many conveyances that nonverbal signals, such as body movements, gestures, facial expressions, gaze, posture, special behavior etc. [5] have is their contribution to interaction adaptation and coordination. Since the adaptation that occurs during human-human interaction is often bidirectional [15], it is important to consider which human behaviors can be adapted or transformed into robot behaviors if robots are to interact with humans in a social manner.

In human social interactions, people tend to mirror and synchronize to the body movement of their interaction partner as a way to coordinate and adapt to each other [12]. Furthermore, research in social and developmental psychology shows that when people interact, their movements tend to become coordinated [78, 103]. When people engage in a joint action, they coordinate their individual actions in order to achieve a common goal [105]. This coordination is also known as interpersonal coordination, which starts to emerge in early childhood and is considered to be the driving force behind successful interaction [78].

In the field of **human-robot interaction (HRI)**, Edwards et al. [32] investigated people's expectations for interacting with a machine-like social robot. They later replicated and extended their work in [31], where a social robot was replaced with a humanoid robot which has a stronger human-like morphology. More specifically, the authors of [31] explored whether participants would report higher uncertainty, lower social attraction and social presence than when expecting to interact with a human and how these initial expectations change after an interaction with a robot. Their results suggest that the morphology of a robot and the initial interaction have an impact on people's expectations of how the social robot will behave/communicate. Actual interaction with the robot exceeded initial expectations. With their results, the authors showed that people generally strive to interact with robots according to the same interaction patterns they use when interacting with other people. In addition, they discuss what they call an anthropocentric expectancy bias, which is the tendency of people to assume their fellow interactants will communicate as humans or human-like and experience a violation of pre-conceived rules when the interactants are less human-like. Therefore, when working on improving a robot's social capabilities, it is important to take into consideration the expectations gap, i.e., the disparity between people's expectations and the actual abilities of the robot [11, 64].

To make robots capable of taking part in social interaction, research regarding the interaction dynamics, the behaviors influencing coordination and adaptation of the interactants' movements, is required (as proposed in [115]), along with the potential of these signals for making an interaction effective and intuitive. This will allow for a better understanding of how a robot and a human can engage in a joint action successfully. Thus, further research is necessary to comprehend in more detail how body movements can aid the motion adaptation and coordination in an interaction between a human and a social robot. One possible approach to the challenge of interaction dynamics is making use of the interaction patterns mirroring and synchrony, which, when combined, make up interpersonal coordination.

1.1 Aims and Scope

In order to support the integration and usage of mirroring and synchrony in the design and implementation of socially competent/intelligent robots, we perform a review of papers that have been published so far in the field of HRI. Past review papers have mainly focused on one [8, 61, 126] or both [121, 127] of these phenomena in the fields of psychology or across several other disciplines [28]. A notable review article in robotics with a specific focus on the application in care was published in [73], where mirroring was referred to as "reciprocity". Our article aims to provide a comprehensive review of papers within the field of HRI that have studied synchrony and mirroring, separately or together, from different perspectives and for different applications.

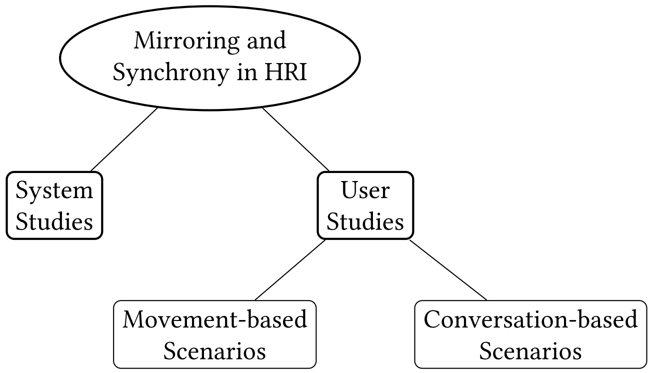

Fig. 1. Tree representation of mirroring and synchrony HRI studies classification.

We employed several search engines and digital libraries such as Google Scholar, ACM Digital Library, IEEE Xplore, and Springer. Important search keywords were "human robot interaction," "mirror," "imitation," "mimicry," "synchrony," "entrainment," and "motor coordination." We selected the articles to meet at least one of the following inclusion criteria: (i) papers describing an imitation of human motion that can potentially be used for mirroring and/or synchrony robotic behavior; and (ii) papers describing experiments where humans are interacting with robots expressing mirroring and/or synchrony behavior.

Brooks [14] has argued for incremental development of robotic behavior, where each behavioral layer adds more complexity to the robot's capabilities. Thus, mirroring and synchrony behavior can be seen as a core layer onto which other complex behaviors can be developed (e.g., learning algorithms). Jordanous [55] reiterated and again advocated for Brooks' [14] approach.

Research regarding mirroring and synchrony in HRI includes two important categories: papers focused on *system studies*, describing technical systems that implement mirroring and/or synchrony behavior, and papers focused on *user studies*, evaluating effects of different experimental conditions with a stronger focus on the human participant. This categorization of research studies is based on [9, p. 132–134], where Bartneck et al. identify the following types of studies in the field of HRI: user studies, system studies, observational studies, ethnographic studies, crowdsourced studies, and single-subject studies. Our review covers user studies and system studies. Additionally, to get an overview of the interaction context diversity in which body movement mirroring and synchrony behaviors of robots have been evaluated, the type of scenarios employed in the user studies is specifically considered. The identified types of scenarios lead to a further split into user studies using *movement-based scenarios* and *conversation-based scenarios*. Figure 1 shows a visual representation of the overall categorization.

In Section 2, we present different definitions and terminology used in the literature to describe the two interactional patterns *mirroring* and *synchrony* in general and in HRI studies. An important aspect when studying these patterns is the morphology of the human body and the embodiment of the robotic platform involved in the interaction. Thus, the body parts that have been the focus of mirroring and synchrony behavior research and the robotic platforms used are reviewed in Section 3. In Section 4, we demonstrate the implementation of the interactional setting in terms of the methods used to extract necessary information from human motion and methods of reacting to human motion. However, the details of the kinematic models used in human-robot imitation systems for translating human body movement to robot body movement are beyond the scope of this review. In Section 5, the methods used to evaluate the technical systems and to measure particular interaction outcomes are discussed. Section 6 features the target applications for the implemented systems and the scenarios used for testing different experimental conditions. Finally, Section 7 provides a discussion and outlines open questions as a guide for future research in the field of mirroring and synchrony in HRI. A comprehensive overview of the included studies can be found in Table 5 towards the end of the article.

2 Definitions and Terminology

The terms mirroring and synchrony are used in the literature to describe behaviors of animate and inanimate objects in different contexts. HRI studies usually rely on mirroring and synchrony definitions borrowed from the fields of behavioral sciences such as social and developmental psychology or neuroscience. As a basic definition, the Collins dictionary describes mirroring as "If something mirrors something else, it has similar features to it, and therefore seems like a copy or representation of it" [22]. The state of being synchronous is defined as "occurring or recurring exactly together and at the same rate" [23]. In movement studies, specifically focusing on dance and movement therapy, mirroring is considered to be an imitation of movement qualities, and it is often used as an exercise to increase empathy among the human interactants [77].

In this review article, we use the definitions proposed by Burgoon et al. [15], in which mirroring, mimicry, and synchrony are considered part of interaction adaptation patterns, as a main framework. These definitions then serve to compare the frameworks used in HRI studies and to provide a general idea of overlaps and divisions in the terminologies used in the selected studies. Furthermore, these definitions provide a good indication about the inclusion criteria of the research papers in this review.

Mirroring is defined as "... the imitation of another's body movements." [15, p. 26].

Mimicry is defined as "... the tendency to imitate others' nonverbal expressions, particularly expressions such as laughter, pleasure, embarrassment, pain, discomfort, and physical exertion.... the process of an instinctual overt reaction that is appropriate to another person's situation rather than to one's own." [15, p. 25–26].

Synchrony is defined as "... individuals coordinate their communication behaviors temporally with those of another conversant to achieve a kind of "goodness of fit" between them." [15, p. 19].

Generally, in literature, the terms mirroring and mimicry have often been used interchangeably. However, Burgoon et al. distinguish the two phenomena by explaining that the emergence of mimicry "requires neither that others be present to witness the display nor that the observer have a prior relationship with the observed". On the other hand, "mirroring is the imitation of another's body movements... posited to serve a bonding or affiliative function and to signal rapport among interactants" [15, p. 26]. Another important concept comes from the work of Bernieri and Rosenthal [12] on nonverbal human behavior. Mimicry and mirroring, or what the authors call behavior matching and interactional synchrony are defined under the same umbrella term *interpersonal coordination*, originating from their contribution to interaction coordination. This behavior is described as "... mutuality, accommodation, and synchrony found in everyday interactional coordination" in [102] or, more concisely, as *interactional synchrony* in the authors' later work [103]. The *chameleon effect* introduced by Chartrand and Bargh [18] is another notion relevant to research on social interaction, and the authors define it as the "nonconscious mimicry of the postures, mannerisms, facial expressions and other behaviors of one's interaction partners," i.e., an unintentional matching of body motion.

Several HRI studies view mirroring and synchrony in the frame of the described interaction system's purpose. For example, mimicking to improve the social intelligence of autistic children [40], synchrony as an essential part of human communication [48], mirroring as a natural behavior (between humans) [39], or the level of synchrony as a reinforcement signal for learning [92]. This

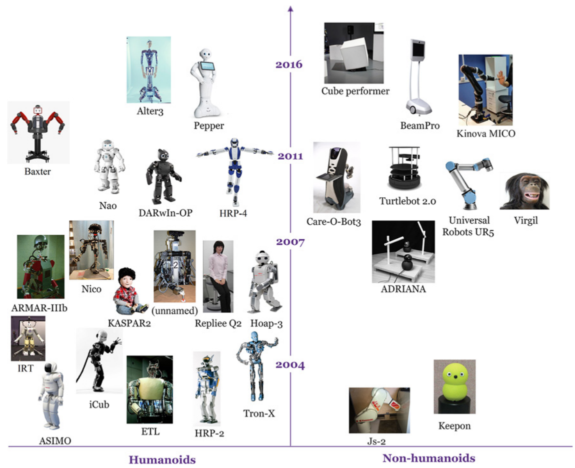

Fig. 2. Robotic platforms used in mirroring and synchrony HRI studies split into two categories, humanoids and non-humanoids, where the y-axis represents the (approximate) year of production. The images are taken either from the related studies cited in the text or from the official pages of the robot manufacturers.

article covers studies within the field of HRI with a focus only on body movement mirroring and synchrony rather than other nonverbal behaviors such as facial expressions.

3 Robotic Platforms and Body Parts

Human bodies and robot bodies are different in many ways. For instance, the material they are made of, the number of joints, the **degrees of freedom (DOF)** in the joints, the speed at which they can move, etc. One of the challenges that emerges from these differences is the relational homomorphism or *correspondence problem* [86], which is defined as how successful the matching between the human motion and the imitated robot motion is. To facilitate the mapping between dissimilar bodies, one common approach in imitation studies is the use of humanoid robots due to their morphology being similar to that of humans (head, arms, etc.). The following subsections provide an overview of humanoid and non-humanoid robots used in mirroring and synchrony studies. Figure 2 shows the robotic platforms used in mirroring and synchrony HRI studies according to the year of production and split into two categories, humanoids and non-humanoids. Table 1 shows the relevant robotic body parts and which robotic platforms were used for the specific body parts.

3.1 Humanoid Robots

The most commonly used platform is the humanoid robot Nao created by Aldebaran,[1] which has a head, torso, two arms, and two legs with a total of 25 DOFs. A possible reason for its frequent use could be the easy access, affordable price, and robot size (58 cm in height), which helps in the evaluations and testing of the HRI system. When testing robot motion with larger humanoids that also have two legs there is the need to consider the balance of the upper body with respect to the lower body. Thus, the space in which the humanoid can move is often constrained by attaching security ropes to the robot, whose purpose is to avoid damaging in case it falls. In mirroring and synchrony studies, Nao has been used for imitation of whole-body movements, which include head, arm and leg movements [66, 69, 91, 114, 133, 136], arm and head movements [62], arm and

[1] https://www.aldebaran.com/en/nao

Table 1. Clustering of Robotic Platforms Used in Mirroring and Synchrony in HRI Studies According to Which Body Parts Have Been the Focus

Body part(s)	Humanoids	Non-humanoids
Whole-body	Nao [66, 69, 91, 114, 133, 136], HRP-4 [25] DARwIn–OP [20, 87], iCub [27, 98], IRT [90]	Keepon [79, 112], Turtlebot 2.0 [54] Cube Performer [41, 42]
Arms and head	ARMAR-IIIb [29], Hoap-3 [40], Nao [62], Pepper [52, 53, 116, 131], ETL [19]	–
Arms and legs	Nao [33, 60, 134]	–
Arms	Nao [1, 4, 39, 45, 48, 83, 84, 117, 125, 132] Nao [3, 130], Alter3 [76], ASIMO [26], HRP-2 [118], KASPAR2 [107, 108], Nico [24], Pepper [50] , Tron-X [63], Baxter [106], (unnamed) [72, 74]	ADRIANA [92], Js-2 [75], Kinova MICO [57], Universal Robots UR5 [94]
Head	Repliee Q2 [109]	Virgil [96]
Torso	Pepper [49]	Care-O-Bot3 [65], BeamPro [21]

leg movements [33, 60, 134], and only arm movements [1, 3, 4, 39, 45, 83, 84, 117, 125, 130, 132]. In studies focusing only on synchrony, Nao has been used to detect an attempt to interact with an interaction partner, by modeling the dynamics of the robot and of an interactant and the use of synchrony detection between the two [47, 48].

In studies that include other humanoids, the upper body, which includes the arms, is the most common center of interest for mirroring and synchrony behavior. The humanoid Nico [24] synchronized to arm movements, Alter3 [76], ASIMO [26], HRP-2 [118], Baxter [106] and Tron-X [63] were imitating arm movements. A human-sized mechanical robot developed in [113] and featuring two anthropomorphic arms has been used to investigate arm movement synchronization in an interaction between the robot and a human [72, 74]. The KASPAR2 robot has been used to study motor coordination of arm movements [107, 108]. The android Repliee Q2 [109] mimicked head movements, while the Pepper robot was used to mirror torso movement [49]. For head and arm movements, the robots Pepper [52, 53, 116, 131], Hoap-3 [40], ARMAR-IIIb [29] and ETL Humanoid [19] have been used. Lastly, the iCub [27, 98] robot DARwIn–OP [20, 87], IRT [90] as well as the HRP-4 [25] robot imitated a human's whole-body movement, which included the head, arms and legs.

3.2 Non-Humanoid Robots

Besides humanoid robots, non-humanoid robots have also mirrored and synchronized to human movement. Keepon [112] has been used to mimic children's expressive motion when dancing with its whole body (nodding, panning, rocking, and bobbing) by using the Effort item from the **Laban Movement Analysis (LMA)**. LMA is a method used in choreography and dance to analyze and interpret whole-body movement according to a few items describing the Body, Space, Shape and Effort [44]. Keepon has also been used to rhythmically synchronize to children dancing using its whole body [79]. In [54], dancing participants were filmed with Kinect cameras, and once certain dance events occurred, a Turtlebot 2.0 robot rolled or turned according to the event. Robotic arms that imitated human arm movement include the Universal Robots UR5 [94], used for teleoperation, the Kinova MICO [57], used for playing a mirror game, and the Js-2 [75], used for rhythm entrainment for rope turning and the ADRIANA robot for a learning system that uses synchrony of arm movements as a reinforcement parameter [92]. The zoomorphic robot Virgil mimicked a human's head gestures [96]. The telepresence robot BeamPro mirrored an interactant's body orientation [21], while the Care-O-Bot3 synchronized its torso orientation to follow the movements of a human [65]. Outside the realm of purely technical works and more situated in the field of art and design, "Cube performer" was used in [41, 42] to obtain the shape of a robot and the corresponding movements of a dancer in an iterative feedback loop.

4 Interaction Implementation

In human social interactions, the behaviors mirroring and synchrony are usually reactions to a particular action in space and time. In related technical systems designed for HRI, two key components are (1) a technique for sensing human motion and (2) a method of reacting to human motion, which is reviewed in the following two subsections, respectively.

4.1 Sensing Human Motion

To study coordination in HRI, a number of different motion tracking methods have been used, which vary in the complexity of the hardware and software components involved. The performance of a variety of motion tracking techniques was thoroughly discussed in [135], where the authors distinguish between the two major groups of visual-based and non-visual-based tracking in the context of rehabilitation systems. A compact review of magnetic, mechanical and optical methods is given in [93]. A survey of computer-vision-based human motion capture can be found in [80], and a detailed review of human motion capture for robotics was presented in [36].

In the domain of non-optical sensors, one approach is to use *inertia* sensors, i.e., **inertial measurement units (IMU)**, which are usually attached to specific body parts or integrated into special suits. In particular, the Xsens suit[2] was used in [27, 60, 114]. A Wii Remote, which also includes an accelerometer, was used to capture arm movements in [107]. A general survey on human motion tracking using inertia sensors can be found in [51], and upper-body motion specifically was addressed in [37]. The advantages of IMUs are the theoretically unlimited workspace compared to optical counterparts and the fact they do not suffer from occlusions. A downside is that the accuracy of the sensed joint positions tends to decrease over time due to mechanical fatigue. In the following, we focus our discussion on optical sensors as they are most dominantly used in mirroring and synchrony studies.

Optical sensors are commonly divided into *optical-marker methods*, which usually consist of several external cameras and wearable markers (active or passive) attached to specific body parts that need to be tracked (e.g., the Vicon systems[3]), and *optical-markerless methods*, which generally are based on the use of a camera (or multiple cameras) in combination with computer vision algorithms. For human motion capture, computer vision algorithms typically target human pose estimation and tracking (e.g., the depth-sensing camera Microsoft Kinect[4] with its own skeletal tracking algorithm). Due to the nature of HRI in a social context, it is important to consider *optical-markerless* human pose estimation due to the increased comfort of the interactant.

A number of works have relied on various types of *optical markers* for the perception component of the technical system [40, 74, 75, 81, 85, 90, 109]. Over the years, Vicon systems have become widely used [29, 59].

[2]https://www.xsens.com/
[3]https://www.vicon.com/
[4]https://developer.microsoft.com/en-us/windows/kinect/

For capturing human motion in an *optical-markerless* fashion, the most widespread approach is the use of the depth-sensing camera Kinect with its human pose estimation algorithm, more specifically, Kinect v2. It is important to note which Kinect version is used due to the difference in accuracy of the joint detection in the skeletal tracking algorithm. The Kinect v2 was found to overall give more accurate joint positions than the Kinect v1 [123]. Kinect v1 has been used in [87, 91, 130, 136], Kinect v2 in [20, 45, 49, 54, 67, 112, 125], and no Kinect version has been reported in [33, 66, 83, 134]. In recent years, the usage of a depth-sensing camera in combination with OpenPose [17], a computer vision algorithm for 2D human pose estimation, has become popular (see an example in [131]).

Summarizing the pros and cons of the three motion capture categories addressed above, it can be stated that methods relying on *optical-markers* excel in terms of accuracy and reliability since measurements of *inertia* sensors can be degraded by drift, and *optical-markerless* methods have to cope with possible errors in joint locations estimated by computer vision techniques. A clear advantage of *optical-markerless* approaches is that no special suits or devices attached to the body are necessary, which allows for natural HRI, comfortable set-up and low costs. *Optical-marker*-based approaches usually require several cameras looking at the human interactant from different viewpoints and are thus demanding in terms of space constraints. A desirable property of *inertia* sensors is their robustness to occlusions. The widespread availability and high potential of *optical-markerless* methods are reflected by the distribution of entries in the "Sensors" segment of Table 5. For all approaches—*optical-marker*, *optical-markerless*, and *inertia sensors*—the estimated/sensed joints are then used to map the human motion into robot motion for synchronous imitation.

4.2 Reacting to Human Motion

The reaction of the robot to the human motion is usually based on an implemented robotic system or remotely controlled by a person. The latter is also known as the Wizard-of-Oz technique, whose introduction is attributed to [58]. A survey on Wizard-of-Oz works in HRI can be found in [95].

System studies, as opposed to user studies, describe and discuss developed technical systems that map human motion into robot motion. As discussed in Section 4.1, the technology used to sense human motion provides human joint positions. Thus, to generate synchronous imitation, a common approach is to map between human joint positions and robot joint angles/positions.

In mirroring and synchrony system studies focused on estimating robot joint angles from human joint positions, the most common approach is to solve the robot's inverse kinematics problem. Generally, in robotics and computer animation, inverse kinematics (IK) is used to calculate all joint angles within a chain that are necessary to move a robot's or an animated character's joints to a given joint position; for example, to move the robot's end-effector (the last joint within a chain of joints allowing the robot to interact with the environment) to a given reachable position in 3D space. The methods used to solve the IK problem include analytical [40, 52, 87, 116, 125, 132, 133], numerical [1, 26, 27, 29, 45, 60, 84, 85, 89, 91, 94, 97, 129, 134], and data-driven/machine learning [33, 59, 66, 114, 131] approaches. Numerical solutions are usually based on iterative algorithms that try to solve the IK problem as an optimization problem, while analytical solutions can be derived in two ways using geometry to find the angle or using algebra to have the angle expressed in equations from forward kinematics. Recent machine learning methods usually employ neural networks to learn the mapping between human joint positions and robot joint angles (or positions) by training on paired human and robot body poses. An advantage of such learning approaches is the potentially easier replicability on different robotic platforms, whereas analytical and numerical approaches depend on the hardware specifications (e.g., the length of the links of a particular body chain) of the target platform. A disadvantage of machine/deep learning techniques is that they may require considerable time and training data to train the network prior to interaction (thus sometimes denoted as data-driven approaches).

Aristidou et al. [6] mention real-time capable solutions for solving IK problems and reproducing human poses abstractly (without a robot) that were published as early as 2004 [43] and 2008 [120]. In a later work, Aristidou et al. [7] discuss the various families of IK solvers, including those that are real-time capable, both analytical and numerical. In the field of HRI, an early real-time capable method was presented by Riley et al. [97], although the authors do not report numbers for the achieved system delay. More recently, real-time solutions have been presented for a variety of commonly used robotic platforms, such as Nao [1, 2, 60, 122, 134], Baxter [106], HRP-4 [25] and Pepper [115]. Analytic solutions can be obtained in less than 50 μs [116, 133], numerical optimization techniques find approximations in times below 5 ms [1, 60, 106], and a recent machine learning-based method reports results within 50 ms [25], although these numbers can vary significantly, depending on the complexity of the robotics platform or kinematic chain.

As opposed to conventional approaches, Zuher and Romero [136] report an attempt to generate the joint angles directly from the sensor by using the estimated rotation matrix, which is available from the OpenNI[5] library for the Kinect camera. However, most of the joint angle values returned by the OpenNI method did not yield sufficient accuracy for their application.

Some studies focusing only on synchrony employ methods for generating synchronous movements based on dynamic systems theories [4, 24, 48, 56, 75, 81]. These methods are based on coupled dynamics and include developing a mechanism for synchronization and motion generation that sees the human and the robot as coupled oscillators. Andry et al. [3], on the other hand, have used a neural network model based on modeling the dynamics of the robot and learning to predict the rhythm of the interactants' motions.

In general, the Wizard-of-Oz method is employed in user studies rather than system studies, and its purpose is to respond to the participant's behavior by controlling the robot with predefined motions without the necessity of human motion sensing. Mirroring and synchrony user studies utilized the Wizard-of-Oz method to control the robot's arm movement [50], the orientation of the robot with respect to the participant [21], the head and upper body movements, such as nodding and pointing [111], as well as speech, head movements and gestures [62].

Some user studies have substituted live experiments of robot interaction scenarios with video-based experiments, where participants watched videos of an interaction between a human and a robot [65, 69]. In [65], the videos included positive and negative robot-to-human movement synchrony, where observers found the robot to be more likeable when exhibiting synchronous motions. In [69], the videos showed "dominant" and "submissive" robot behavior where observers judged it to be less trustworthy in the former case. The assignment of the aforementioned works to their respective mapping categories is also shown in the "Mapping" segment of Table 5.

5 Evaluations and Outcome Measurements

When designing and developing a technical system that allows a robot to mirror and synchronize to human movement, system evaluation is an important step in the overall process. This step contributes to making sure that the implemented system works as intended before using it in a user study and also provides information that can be used for comparison with related existing systems. Similarly, when studying how people respond to a mirroring and synchrony behavior expressed by a robot in a user study, the method of measuring an interactional outcome or attitude towards the robot is an important step. In this section, methods used to evaluate system performance and measure outcomes of mirroring and synchrony in HRI are reviewed from both perspectives. Thus,

[5]https://structure.io/openni

for system studies, the focus is on the evaluation of technical characteristics such as a technical system's accuracy and efficiency, while for user studies, the central questions are what interactional outcome or attitude towards the robot is being measured and how it is measured. The works discussed in this section are also listed in the "Evaluation" segment of Table 5.

5.1 System Studies

Mirroring in system studies is described as the ability to imitate human body motion, while synchrony is described as the ability to synchronize to human body motion, in some cases in combination with other modalities (e.g., audio [24]). We can identify two important aspects of motion that are typically included in the evaluation process: (1) *form-related* metrics to assess the similarity between the human pose and the imitated pose for mirroring, and (2) *time-related* metrics to assess the temporal characteristics of the imitated movement for synchrony.

These two aspects can be evaluated using quantitative methods, qualitative methods or a mixture of both approaches. Studies also occasionally report subjective measurements, as described by Bartneck et al. [9, Chapter 9]. When using subjective methods in system studies, the technical aspects of the regarded system are described, and it is then evaluated with a small user study (for example, assessing the quality of the imitation [136]). Since subjective measures are mentioned only in a few system studies, the following subsections will focus and review the evaluation approaches used in the context of quantitative and qualitative evaluation methods. Table 2 shows an overview of the methods used to evaluate the form and time features of different systems reported in studies covered by this review.

5.1.1 Quantitative Evaluation Methods. Quantitative evaluation methods and metrics for *form-related* features include the calculation of the mean squared error between the target and actual end-effector trajectories [1, 33, 45, 116, 118, 132, 134] and pose similarity metrics which can be measured using cosine similarity for angular configurations [1, 45, 132]. In addition, Zhang et al. [134] report the mean deviation between targeted versus actual joint positions for specific motions and Zabala et al. [131] report jerkiness and length of the generated trajectory paths, with jerkiness as a smoothness measure based on the acceleration derivative [16]. Zhang et al. [133] compute a similarity index, a correlation coefficient between two vectors, as well as joint angle errors, which are also addressed in [97]. For *time-related* features, common metrics are the synchronization index [54, 81], system delay [132] and related event-based metrics [54, 85]. Frequency synchronization [47, 75], energy transfers [75], and reinforcement learning signals [92] have been utilized in the past, while in more recent works, entrainment modes [83] or explicit memory transfers of motor commands [76] are presented. A number of works also report computational effort/cost [33, 45, 60, 133] or similar metrics describing the required computational resources of the investigated systems (e.g., execution cycle times [19], calculating time [40, 134]). For robotic systems focusing only on synchrony, the synchronization index or mean phase coherence is commonly reported [54, 81, 82].

A particularly interesting example of the quantitative evaluation of *form-related* features, specifically the pose similarity between a human pose and the imitated robot pose, is the method proposed by Lei et al. [66]. The authors reduce the human and robot motion space to a combination of shared space and personal space, which allows them to regard the task as a dimensionality reduction problem which is related to the unsupervised method of Wang et al. [124].

Evaluations of mirroring and synchrony behavior often incorporate visualization techniques for *form-related* features, such as trajectory plotting of the X, Y, and Z coordinates of the end-effector position or other joints angles [1, 27, 33, 52, 66, 84, 87, 91, 100, 119, 130, 132, 133], as well as the position error [29, 60] over time.

Table 2. Overview of Form-Related and Time-Related Features and Corresponding Metrics Used in Quantitative and Qualitative Evaluation Methods in Mirroring and Synchrony System Studies

	Quantitative	**Qualitative**
Form-related	Mean squared error or Euclidean norm of targeted versus actual end-effector trajectories [1, 33, 45, 116, 118, 132, 134] Key joint angle errors [97, 133] Visualizing position deviation over time [29, 60] Plotting trajectories of end-effector or joint positions or angles over time [1, 27, 33, 52, 66, 84, 87, 91, 100, 119, 130, 132, 133] Cosine similarity [1, 45, 132] Pose distance metrics [66, 124] Multi-facetted similarity index [133] Jerkiness and length of generated trajectory [131]	Images of imitation of a human side by side with a virtual robot [1, 20, 59, 84, 87, 118, 129, 131] Images of imitation of a human side by side with a physical robot [19, 29, 60, 85, 122, 125, 133, 134] [33, 40, 56, 63, 90, 97, 116, 119, 136] Images of imitation of a human side by side with a physical and a virtual robot [20, 27, 45, 66, 91, 129, 130, 132] [26, 29, 76, 89] Videos showing imitation results with a physical [1, 76, 91, 94, 114] or a virtual robot [131]
Time-related	Modes in entrainment [83] Reinforcement signals [92] Computational effort [19, 33, 40, 45, 60, 133, 134] Memory transfers and motor commands [76] Synchronization index [81] or event frequency [54] or event correlation [85] or oscillation periods [83] Angle trajectories [100] or frequency synchronization [47, 75] over time Energy transfers [75]	

In the context of synchronization, visual evaluation methods for *time-related* features include angle trajectories plotting of a human and robot synchronization in a simulated interaction [100] and visual representation of a human and robot motion frequency synchronization over time [47, 75]. Furthermore, when synchrony is used as a feature to support learning, the evaluation includes plotting of the difference between real and predicted human actions (phase shift) [3, 92].

5.1.2 Qualitative Evaluation Methods. Qualitative evaluation methods are typically images of a human pose and the imitated pose of either a virtual (simulated) robot [1, 20, 59, 84, 87, 118, 129, 131], a physical robot [19, 33, 40, 56, 60, 85, 90, 97, 116, 119, 122, 125, 133, 134, 136], or both [26, 27, 45, 66, 76, 89, 91, 129, 130, 132]. Some papers also include a link to a video as a way to show the results of the reported interaction system where usually a human performs a few motion sequences which are imitated by the robot [1, 76, 91, 94, 114, 131].

5.2 User Studies

In user studies related to mirroring and synchrony in HRI, the outcome measurements depend on the assigned dependent and independent variables. The dependent variable depends on the behavior of the participant, and it is a variable that is being measured as an outcome within a study. Contrary,

Table 3. Overview of Outcome Measurements in Mirroring and Synchrony User Studies and the Evaluation Methods Used in Terms of Quantitative and Qualitative Measures

Evaluated outcome	**Quantitative evaluation**	**Qualitative evaluation**
Impression of the robot [39, 50, 65, 109, 111] of the interaction [21, 96, 112] of both the robot and the interaction [49, 57, 62, 69, 107]	Questionnaires [21, 39, 49, 50, 57, 62, 65, 68, 96, 107, 109, 111] Engagement, energy level [112]	Behavior observation [39, 79] Interviews [96] Open-end questions in questionnaires [21, 49]
Occurrence of mirroring and synchrony or (un-)intentional coordination between a human and a robot	Questionnaires [54] Interaction time [79, 92, 112] or delay [3] Velocity, lag variability and dwell times [73, 81] Amount of body movement [49, 112]	Behavior observation [79, 81, 92, 112]

the independent variable is independent of the participant's behavior and, therefore, is the one that varied among conditions. Mirroring and synchrony have been studied both as dependent [50, 72] and independent [21, 39, 49] variables.

In the case of a dependent variable, the research focus usually is on whether or not mirroring and synchrony occur in an interaction between a human and a robot. For example, when a human and a robot are performing a specific movement task, studies [72] and [50] explore whether their movements get synchronized. Thus, the outcome measurements are usually methods of determining the occurrence of mirroring and synchrony between a robot and a participant.

In the case of an independent variable, the focus of research is usually on how people respond to a robot expressing mirroring and synchrony behavior within an interaction and thus the measurement is an interaction outcome or an attitude towards the robot. These outcomes are usually borrowed from research on human interactions in the field of social psychology, where studies often include outcomes that can be evaluated with interpersonal or intrapersonal measures. Interpersonal measures include the evaluation of the overall interaction, the judgment of the interaction partner, and prosocial behavior, whereas intrapersonal measures refer to personal experiences or emotional states during the interaction, such as anxiety, mood, etc. [121]. In this context, movement coordination has been found to have an effect on specific interaction outcomes such as rapport, smooth interaction, degree of liking, closeness, and similarity between interactants [121]. Similarly, in HRI studies, some of the outcomes include likeability towards the robot [39, 109], perception of the overall interaction [62, 96], and perception of the robot [49, 62, 69, 111].

The methods used to evaluate the outcome in both cases (mirroring and synchrony as dependent and independent variables) include quantitative, qualitative, or a mix of both methods. The following subsections describe in more detail the outcome measurements found in the literature in terms of quantitative and qualitative evaluation methods. Table 3 shows an overview of the outcome measurements found in the user studies included in this article and the methods used to measure them.

5.2.1 Quantitative Evaluation Methods. Mirroring and especially synchrony as an independent variable have been used to investigate the effect they have on the user's impression of, or likeability towards, the robot [39, 49, 65, 109, 111], the user's general impression of the interaction [21, 49, 96] or combining both aspects [62, 107]. These outcomes are typically measured quantitatively using questionnaires, also known as Likert scales [70].

The commonly used Godspeed questionnaire [10], employed in many mirroring and synchrony user studies [39, 49, 50, 57, 65], measures a robot's perception among five main items, namely anthropomorphism, animacy, likeability, intelligence, and safety. In the questionnaire, each of these items is measured by rating several attributes on a scale from 1 to 5. For example, an attribute of both perceived animacy and anthropomorphism refers to how artificial or lifelike the robot is, with rating 1 meaning artificial and 5 lifelike. The advantage of using the Godspeed questionnaire is that it allows for comparison among studies, thus it has become a common tool for quantitatively evaluating how a robot is perceived when testing or comparing specific functionalities.

Besides Godspeed, other validated and known questionnaires have been used in the literature. For example, to measure specific perceived robot attributes [109, 111], aspects of the interaction with [49] or via [21] the robot, or both perceived attributes and interaction [62, 68]. In addition, it is also possible to develop a custom questionnaire, like it was done in [107] and [57], which measures both the perception of the robot and the interaction. Rueben et al. [99] provide recommendations regarding the correct usage of questionnaires ("scales") and their (re-)validation.

When synchrony and mirroring are studied as dependent variables, examples of quantitative evaluation methods include the use of a questionnaire that asked participants to rate which of the two dance sessions that they took part in felt more synchronous [54]. The time until learning converges, in cases where synchrony was used as a feature for intuitive demonstration of an action for the robot to learn, and the delay between human and robot motions was reported in [3, 92]. Other methods in this category focus more on temporal aspects, such as measuring the total time of interaction [112], event prediction/velocity [81], lag variability/dwell times [74] and oscillation periods [83]. The percentage of dwell times is usually used to evaluate relative phase stability (dwell times represent the relative phase indicating in-phase or anti-phase synchrony). Further related techniques focus on body aspects and include gesture and behavioral analysis [62, 79, 96, 110] or the amount of body movement [49, 112]. Other quantitative evaluation methods include measuring group synchronization in the context of dance [54] and synchrony using an information distance measure for 3D trajectories [107].

5.2.2 Qualitative Evaluation Methods. Qualitative evaluation methods, when mirroring and synchrony are studied as independent variables, including discussions between the robot and participants [39, 96], behavior observations [79, 112], interviews about the impressions of the interaction [96] or the robot itself [49] and open-end questions in questionnaires regarding the overall interaction [21]. When synchrony and mirroring are studied as dependent variable, qualitative evaluations can also include behavior observation [79].

5.2.3 User Studies Demographics. Table 4 summarizes demographic information on user study participants derived from papers that report it. From the figures listed in the table, the average mean age across studies is 25.7 years, with a gender split of about 40% females to 60% males.

A number of studies stand out due to their noteworthy demographics or their specific context: Participants in [24] were musicians playing the drums with a human conductor. The robotic system described in [79] interacted with the open public, mostly children. In [98] the participants included couples with infants at the age of 8 to 30 months. Fujimoto et al. [40] investigated the effects of an imitation system on children diagnosed with autism. Simmons and Knight [112] focused on the interaction of children and dancing robots.

Table 4. Demographics of Participants for User Studies

		[108]	[96]	[39]	[69]	[62]	[111]	[21]	[38]	[50]
Partic-ipants	Total	24	12	40	56	90	80	36	20	45
	Female	8	6	9	28	59	11	18	10	30
	Male	16	6	31	28	31	69	18	10	15
Age (Years)	Range	21–50	19–70	19–35	18–31	17–48	18–24	18–44	20–48	18–31
	Mean	28.1	32.1	21.7	20.3	21.9	21.8	22.8	26	20.5
	Std.dev.	6.95	14.5	3.05	2.0	4.47	0.93	5.82	5.8	2.7
		[48]	[72]	[81]	[65]	[54]	[117]	[49]	[73]	[109]
Partic-ipants	Total	15	8	12	119	27	61	20	6	65
	Female	7	4	9	36	14	12	2	2	27
	Male	8	4	3	83	13	49	18	4	38
Age (Years)	Range	18–25	–	20–48	22–76	–	–	–	20–28	20–49
	Mean	–	28.8	30.8	35.3	22.9	29	23.4	23	–
	Std.dev.	–	–	–	–	3.98	7	–	–	–

6 Applications and Scenarios

In mirroring and synchrony HRI studies, it is fundamental to determine the application of the investigated human-robot system and the interaction context or scenario it is intended to be used in. This is relevant for making technical decisions because depending on the application or scenario, different requirements might apply.

Applications in system studies are important because they support the motivation of building such interaction systems. Scenarios in user studies, on the other hand, are important because they provide a setting where mirroring and synchrony can be studied in order to gain a better understanding of their role in interactions. Furthermore, the scenarios used in user studies also need to be carefully considered with the application of the human-robot system in mind. That way it is ensured that the used measures and metrics are suitable to make certain conclusions about what the examined interaction system can contribute to the HRI research field.

This section reviews the applications reported in system studies and the scenarios that are used in user studies to measure certain outcomes. The covered studies can also be found in the "Scenario" segment of Table 5.

6.1 Target Applications in System Studies

The most common application of synchronous imitation systems is imitation learning or also known as learning from demonstration or programming by demonstration. Thus, human-robot imitation has been inspired by imitation as a social learning concept [133], which allows for a quick and natural approach to programming human behaviors for humanoid robots [125]. Learning by imitations has also been proposed as an important feature for cognitive development in robots [101] and as a means to teach robots human-like motions [33, 87, 90, 119, 122]. Imitation learning has also been proposed for more specific tasks, such as teaching robots conversational movements synchronized with the flow of speech [131].

Another common application is imitation as a way of implementing human-like behaviors. It is argued that imitation is a promising method for effective and intuitive creation of human-like behaviors [97], while also preserving the goal-directed characteristics of the movement [29]. It has also been used as a means of translating human motion as closely as possible to robot motion by generating human-like motion within the physical capabilities of the robot [118]. The

Table 5. Summary of Studies Included in This Review Article Organized by the Focus of Study, Body Part Focus, Use of Sensors, Mapping Technology, Evaluation Method, and the Scenarios Used

		Focus of study	
		System	User
Body part	Whole-body	[20, 25, 27, 53, 59, 66, 69, 85, 87, 90, 91, 98, 114, 129, 133, 136]; non-hum.: [41, 42]	non-hum.: [79, 112]
	Arms and head	[19, 29, 40, 52, 62, 116, 131]	–
	Arms and legs	[33, 60, 134]	–
	Arms	[1, 26, 45, 63, 75, 84, 106, 118, 125, 130, 132]; non-hum.: [24, 72, 94]	[3, 4, 39, 48, 50, 76, 83, 117]; non-hum.: [57, 67, 72, 74, 81, 92, 107, 108]
	Head	–	[96, 109]
	Torso	[54]	[49]
Sensors	Optical markers	[29, 40, 75, 85, 90, 97, 129]	[108, 109]; non-hum.: [73, 81]
	Optical markerless	[1, 19, 20, 26, 33, 45, 59, 63, 66, 84, 87, 91, 98, 125, 130, 131, 132, 133, 134, 136]; non-hum.: [24, 94]	[3, 4, 39, 48, 49, 53, 76, 79, 83, 96, 117]; non-hum.: [54, 57, 67, 72, 92, 112]
	MoCap/IMU/Force	[25, 27, 33, 60, 89, 107, 114]	non-hum.: [71, 72]
	Other	non-hum.: [24]	[4, 48]
Mapping	Analytical IK	[19, 40, 52, 87, 90, 116, 125, 132, 133]	–
	Numerical IK	[1, 26, 27, 29, 45, 60, 84, 85, 89, 91, 97, 118, 129, 134]; non-hum.: [94]	–
	Data driven	[33, 59, 66, 114, 131]	–
	Wizard-of-Oz	–	[50, 62, 110]
	N/A	[20, 63, 130]; non-hum.: [24, 100]	[76, 83, 107, 117]
Evaluation	Quantitative	[47, 52, 54, 75, 114]; non-hum.: [94, 100]	[3, 4, 24, 38, 39, 48, 49, 50, 52, 62, 69, 76, 83, 107, 108, 109, 110, 117]; non-hum.: [21, 41, 54, 57, 65, 67, 72, 74, 81, 92]
	Qualitative	[19, 20, 59, 63, 87, 118, 125, 129, 130]	–
	Both	[1, 26, 27, 29, 33, 40, 45, 56, 60, 66, 76, 81, 83, 84, 85, 89, 90, 91, 92, 97, 116, 119, 124, 131, 132, 133, 134, 136]	[53, 96]; non-hum.: [79, 112]
Scenario	Movement	[1, 3, 26, 27, 29, 33, 52, 59, 75, 84, 85, 87, 90, 92, 97, 98, 114, 118, 119, 122, 130, 136]; non-hum.: [24, 79, 94]	[3, 4, 38, 40, 48, 50, 52, 53, 107, 108, 117]; non-hum.: [41, 54, 57, 65, 67, 72, 79, 81, 112]
	Conversation	[98]	[39, 49, 62, 69, 96, 109, 111]; non-hum.: [21]

The default type of robot is humanoid; in works marked with "non-hum.", the robot is non-humanoid.

concept of mimicry is also used as a natural way to teach human-like behaviors to robots [1]. An interesting and rather specific application of a reported HRI system is imitation of dance movements found in [85].

Teleoperation has been envisioned as a way to directly control robots from observations of human motion [26, 59, 84]. Using mimicry as a concept to achieve more effective and intuitive teleoperation, especially for novice users, has been suggested in [94]. Also, teleoperation has been proposed with a combination of virtual reality to ease the process of learning from demonstration [52] and as synchronous generalized remote control designed for multiple robotic platforms [27, 114, 130]. Teleoperation in combination with recognition of specific human motions that trigger robot behaviors has been studied in [136]. For example, recognizing the human performing a swipe gesture results in the robot performing a hello gesture.

On the other hand, system studies describing a technical system that can only synchronize to but not mirror human body motion include applications such as motor coordination in joint human-robot action [75], social learning [3, 92], modeling attention via synchrony [98], and synchronization in social tasks [24, 79].

6.2 Scenarios and Interaction Context in User Studies

As user studies usually make use of a mirroring or synchrony system in an interactive setting, it is necessary to design scenarios that allow for testing in the specific interaction context. A possible purpose of such user studies is to explore how mirroring and synchrony affect the human perception of the robot: for example, its likeability [50, 109], the impression of dominance [69], or a good general impression [49, 65]. Other studies seek to investigate the impact on HRI and communication: for example, by fostering engaging interactions with participants synchronizing to the agent [108], by strengthening human-robot partnership [38], or by facilitating adaptive interaction [107]. Some mirroring and synchrony user studies also target the feelings of the human interactants, for example, by investigating closeness [21] or rapport [39, 96]. Another goal is the stimulation of resulting actions: for example, by providing motivation for helping [110]. Examples of specific applications include the interaction with a dancing robot [112], the support of physical rehabilitation [67] or the behavioral analysis of children's interactive involvement with a robot via dancing [79].

Based on interaction settings found in the literature, we split the scenarios into two categories: *movement-based* and *conversation-based*. By movement-based scenarios, we mean the use of an interaction setting based on movement tasks, where the participant and the robot are moving in a particular way, while conversation-based scenarios include the use of an interaction setting based on communicative tasks between the robot and the participant. To get an overview of the interaction context in which body movement mirroring and synchrony have been explored in HRI user studies, the following subsections look into how scenarios of these two categories have been set up and employed. Figure 3 shows a tree representation of the split of scenarios used in user studies.

6.2.1 Movement-Based Scenarios. Movement-based scenarios in mirroring and synchrony studies include child-robot interactions such as a robot dancing with children [112] and a robot teaching a motion task which has to be imitated by a child [40]. Some studies have used video-based interaction rather than live interaction as a method of measuring an outcome. An example of such a study is described by Stolzenwald and Bremner [117], where the video shows two humans performing a similar gesture and a robot imitating one of them so the participants could choose which human the robot is imitating. Gemeinboeck et al. [41] investigate the emergence of the social presence of a robot through movement. A particularly interesting study is presented by Kashi and Levy-Tzedek [57], where the authors make use of the Mirror Game as an interactive scenario. The Mirror Game [88] is a dyadic movement game used as a warm-up activity in the theater where two interaction partners (A and B) mirror each other's movement. The game has two modes: (1) leader-follower,

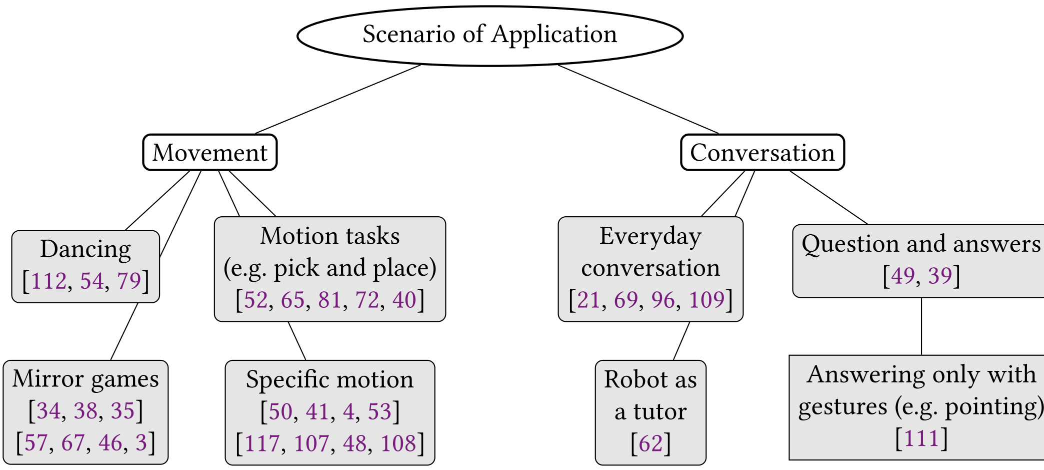

Fig. 3. Diagram showing different movement-based and conversation-based scenarios used in user studies of mirroring and synchrony in HRI. Works are sorted chronologically (descending) within each field.

where either A leads and B follows or B leads and A follows, and (2) joint-improvisation, where there is no designated leader, thus A and B move together while maintaining the mirroring behavior. This game is relevant because it allows for movement-based interactions with no limitation on specific body parts or movement range, and recently, it also started getting attention and interest from research in human interaction. For example, it has been used to study the dynamics between two people, such as their movement synchrony [34] or to play hand-clapping games [38], the feeling of individuality versus togetherness in joint improvisation [46], correlations between people's mutual attachment and their nonverbal behavior [35] and behavior perception of a robot [3, 107], in a leader-follower setting [57], or for movement rehabilitation [67].

Synchrony has been studied with scenarios with joint action tasks where a robot and a participant are sitting opposite on a table and performing pick and place tasks [72, 81]. Other scenario settings include instructing a participant to perform arm movements, such as moving their arm in a circular motion while sitting next to a robot that also moves its arm in a circular motion [50]. Arm movement scenarios also include a participant standing opposite of a robot and both moving their arm horizontally, vertically, and waving at each other [4], or both a robot and a participant moving their arm in an oscillatory manner but not necessarily performing the same arm movement [48]. In [52], teleoperation of a robot with a virtual reality setup was developed while paying attention to user preferences. Different motion patterns to increase familiarity with the robot were experimented with in [53]. Shen et al. [108] instructed participants to wave with horizontal arm movements, using only the forearm while observing a robot, a pendulum, and a virtual moving dot, all moving with the same speed producing wave-like motions. Fitter and Huchenbecker [38] used clapping games in a study where a robot and a participant standing opposite of each other performed repeated claps with their opposite hand. In addition, a video-based study used a video showing a human arranging flowers in a vase while a robot was observing and moving in response to the human in a home environment [65]. Dance scenarios for movement coordination were showcased in [54] and [79].

6.2.2 Conversation-Based Scenarios. Conversation-based scenarios in mirroring studies include participants answering predefined questions asked by a robot [39, 49] or describing a route they took to get to the lab and more personal information, such as their first memories of the city they live in to a robot [96]. In [62], a robot talked about a specific topic and asked a participant questions as a role of a tutor. In [111], both a robot and a participant were answering questions only with nonverbal behavior (e.g. nodding for yes, or pointing to a picture to show the correct answer). Other scenarios include a conversation setting for getting to know each other between a confederate using a telepresence robot and a participant [21] or a robot giving a speech with the participants listening and judging the experience [109]. Li et al. [69] used video-based interaction rather than live, and the video showed a robot and a human having an everyday conversation, in which case the robot was imitating human's movements, but also the human was imitating robot's movement.

7 Discussion and Future Work

Based on the previous findings, we now discuss several noteworthy aspects of the reviewed studies that we identified for further consideration. While some suggestions for future work arise already as part of the discussion in Section 7.1, we further point out open questions and relevant trends in Section 7.2, followed by concluding remarks in Section 7.3.

7.1 Critical Discussion

A major current challenge of mirroring and synchrony in HRI is the only weakly established link between the technical systems reported and the use of them in user studies. A better understanding of the technical systems to explore the attitudes of people towards robots or interactional outcomes would reduce the discrepancy between what is technically feasible and people's expectations of what is possible. To this end, we recommend incorporating mutual support between the technical and user perspective into the design of system studies. This could be implemented at different levels. For example, a Wizard-of-Oz study should be accompanied by a discussion of the technology gap between the simulated HRI system and the actual state-of-the-art to convey its proximity to realization. Another possibility would be to analyze in more detail the deviations in responses between subjects with and without engineering background in user studies, which may shed further light on possible technology-induced biases. Generally speaking, our recommendation calls for collaboration and inclusion of different disciplines, something that is already deeply rooted in the conception of HRI, and that is only starting to become a practice.

Given the classification of system studies and user studies, which we adopt in the review, we can identify some challenges for each. In system studies, one of the current challenges that should be considered is finding quantitative and qualitative evaluation methods of system evaluation that allow for better comparison between different systems. We recommend that the evaluation should also include subjective measures, especially with movement experts (e.g., professional dancers, sports players, physical therapists, animators), since they have a good understanding of human movements and how they could be translated into robot movements. An iterative approach of developing and testing the robotic mirroring or synchrony system with user studies should help with making certain technical and design decisions. Furthermore, evaluation methods in user studies should also be improved and expanded to include a mix of different evaluation methods. As Riek et al. [96] recommend in the context of affective HRI, better methods for evaluating the interaction between a robot and a human need to be created by developing new metrics to measure interaction outcomes. The authors make this suggestion because the questionnaire they used (taken from human interaction) did not yield any significant results in their human-robot imitation study. Bethel and Murphy [13] suggest using at least three methods of evaluation to ensure more valid and reliable results. More recently, Rueben et al. [99] recommend that existing scales should be validated in a similar study to the one they were designed for, whereas inadequate scales should be modified and re-validated to ensure validity and efficacy. So far, self-assessment (via questionnaires) is the most common evaluation method in mirroring and synchrony user studies (also visible from Table 3), sometimes used by itself or in combination with behavior observation.

Considering ethics, a point that has not been addressed is the concerns about the deceptive behavior of robots, more specifically, whether it is ethical for a robot to express social intelligence or skills in the same way humans do. If the robot shows human-like abilities which cannot really be expressed by inanimate objects, how can we make sure that the human is not subject to deception? The reasoning behind this comes from research in human interactions, where mirroring and synchrony behavior can be linked to an increase of likeability and rapport between interactants [121]. Krämer et al. [62] found that mirroring behavior is not always noticeable by humans, which indicates the importance of the further investigation to assure transparency and avoid possible deception. The implications of deceiving users in HRI are discussed by Wynsberghe [121] in the context of care ethics. The author raises concerns about the role of reciprocity in human-robot care interactions, with the aim of supporting human care providers. Related questions could also be incorporated into future mirroring and synchrony interaction studies.

7.2 Open Questions and Trends

As regards human motion sensing, optical-markerless systems are expected to gain further importance and widespread usage in mirroring and synchrony applications. This trend is driven by strong progress in the fields of computer vision and machine/deep learning in recent years, which enables increasingly accurate estimation of 2D and 3D human joint locations from low-cost RGB cameras. Conceptually, this can be regarded as a shift from relatively costly sensing hardware to cheap cameras in conjunction with software algorithms and learned models that draw knowledge from training on large datasets. With the success of deep learning models and their adoption in HRI research, the acquisition of annotated datasets for usage in training and evaluation of human-robot mirroring and synchrony scenarios is becoming particularly important.

The chosen human motion sensor and the applied human-robot mapping technology are often presented independently of each other in the reviewed studies. A more holistic view could reveal possible inter-dependencies between them. In particular, errors in captured human joint positions might be suppressed or emphasized by the subsequent mapping process. The extent to which these combined effects influence the measured quality of the overall imitation or synchronization system would be an open question for future research and further the identification of meaningful trade-offs in system design.

While human motion capture can clearly benefit from state-of-the-art deep learning models, a largely open question is which other modules of a mirroring or synchrony pipeline—for example, the mapping from human to robot motion—should also incorporate learning-based techniques. On the one hand, one could argue that well-established models, such as for inverse kinematics, are not promising candidates for replacement by data-driven approaches. On the other hand, a current trend towards end-to-end learning suggests a human-robot imitation or synchronization system where a suitable robot mirroring action is learned from a sufficient amount of paired human-robot motion samples. However, the acquisition of such annotated datasets is usually time-consuming but can possibly be alleviated by cross-transfer between different robotic platforms.

Safety in human–robot interaction is a particularly important topic to tackle in future research. While Dragan et al. [30] study the legibility and predictability of robot motion in human-robot collaboration, Sciutti et al. [104] argue that mutual adaptation during the interaction can make the robot more legible and predictable to the human partner. Following this idea, mirroring and synchrony—which facilitate the adoption and reproduction of human movement patterns by the robot—could, in turn, make the robot motion easier to interpret and anticipate by the human, thus fostering safety in joint human-robot actions.

Other challenges that need to be considered for future research are imposed by dealing with human data and ethical aspects arising from the interaction itself. This includes finding ways of informing the human interacting with a robot about how their data is used. Human movement data captured during mirroring and sychrony interactions contain person-specific movement patterns or styles whose characteristics may enable the identification of individuals. Privacy of such personal data is a substantial part in the process of developing transparent and ethical technologies. So far, the studies included in this review normally do not discuss how human data is or will be handled.

7.3 Concluding Remarks

In this review article, we focused on mirroring and synchrony behaviors usually found in human interactions and laid out the HRI studies that, in some way, have explored these two phenomena either from a technological perspective or in an exploratory way. With the growing importance of nonverbal behavior in HRI research, mirroring and synchrony are expected to receive increased attention in the future as promising skills for robots to effectively and safely interact with humans. We addressed technical questions of the human-robot motion transfer and focused on important aspects of HRI for the evaluation of robotic systems as well as user studies. Suggestions for improved evaluation strategies and the growing influence of deep learning methods on the development of human-robot mirroring and synchrony systems were among the points identified for future action.

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