Discover Artificial Intelligence

Perspective

Systems of collaboration: challenges and solutions for interdisciplinary research in AI and social robotics

Frauke Zeller[1] · Lauren Dwyer[1]

Received: 21 February 2022 / Accepted: 2 June 2022
Published online: 20 June 2022

Abstract

This article examines the challenges and opportunities that arise when engaging with research across disciplines, contributing to the growth of social robotics and artificially intelligent systems. Artificial intelligence has a significant role to play in human–machine communication; however, there are barriers to its adoption and considerations towards systematic implementation for the good of people and societies. This perspective piece considers the position of artificial intelligence in systems of human–machine communication. The study of artificial intelligent systems is one of discovery, trial, and error through a melting pot of methodologies, and this interdisciplinary nature is explored through the perspective of researchers at the centre of collaboration coming from artificial intelligence, robotics, and communication.

1 Introduction

The function of artificial intelligence (AI) in the interaction between humans and robots is rooted in communication, with humans, the environment, or even other machines. Combining theories of human–robot interaction (HRI) and traditional communication studies, this perspective piece applies a human–machine communication (HMC) framework that considers the complexities of knowledge generation and measuring success in an interdisciplinary field. Conclusions drawn by way of design and testing are dependent on the methods used to derive them; following standardized methodologies set out by contributing fields of study can be crucial to the success of a researcher in publishing, generating discourse, and achieving functional design [1]. This creates challenges for interdisciplinary teams: while classic research methodologies are proven through time and repetition, this does not necessarily make them the most effective for the future of their fields [2, 3]. With the evolution of interdisciplinarity in AI, specifically in applications for robotic systems, the boundaries surrounding methodologies and standardized practices are becoming blurred, leaving space for new and more creative methods to grow [3, 4]. This article examines the challenges and opportunities that arise when engaging with research across disciplines contributing to the growth of artificially intelligent systems in social robotics. Moreover, we address systemic AI by looking into how research around AI-enhanced social robotics is impacted and how an interdisciplinary point of departure can provide a holistic and synergetic research and development approach. We are starting, thus, with social robotics as an AI-enhanced system, to then explain how the field of Human–Robot Interaction connects to Human–Machine Communication, and how the latter represents a core approach that can combine both AI and social robotics research. In a more applied step, we then introduce how interdisciplinary research—with contributors from HMC, HRI, AI and other fields—can work despite challenges and risks.

Frauke Zeller, fzeller@ryerson.ca; Lauren Dwyer, lauren.dwyer@ryerson.ca | [1]Toronto Metropolitan University, Professional Communication, Toronto, ON, Canada.

1.1 AI-enhanced social robotics

Social robotics is a subfield of HRI that examines the design and testing of robots whose primary function involves the interaction with humans on a social level, rather than simply acting as tools for human use [5]. In other words, a social robot is expected to not only complete the actions and roles of traditional robots but to further incorporate behaviour and communication that allows for human–machine communication prioritizing human perspectives [6, see also 7]. Incorporating multimodal interaction methods such as Sense-Act-Modulated-by-Interactions (SAMI) allow social and companion robots to prioritize human understanding in communication [8] Social robots, unlike their industrial counterparts, rely heavily on (emotive) feedback from the human user to achieve standards of sociality and therefore provide seamless and improved interaction [9]. This, in turn, is also thought to improve human acceptance of such robots, which represents one of the main objectives in HRI [10, 11], and has implications for the use of standardized computer science metrics that fail to address the social aspects of HRI design and testing [4, 5]. Past research has increasingly focused on building social robots that are similar to humans in both their physical design and their emotive and behavioural aspects, particularly in mirroring of human communication methods such as speech and facial expression [9]. This means that the traditional focus in HRI—physical interaction—has been shifted to the social dimension, or at least integrated the social dimension as a benchmark-like feature. Arguably, this shift provides new opportunities for innovation due to its broader, less fixed demarcations. At the same time, it also challenges our HRI approach by integrating a complimentary approach, which is instilled by both technology and social interaction aspects. Hence, Tapus, Matarić and Scassellati [12] describe this field as:

The study of human-robot interaction (HRI) [...] is a new, interdisciplinary and increasingly popular research area that brings together a broad spectrum of research including robotics, medicine, social and cognitive sciences, and neuroscience, among others [12].

Social robots are defined by their ability to interact with human users in a way that generates social interaction. In both instances, the physical and technical dimension, which was originally one of the core dimensions in HRI and represented in the discussions around the embodiment concept, is today less central. In fact, embodiment and environmental interaction now take a lower priority in the role of social robots, with emphasis shifting to other social features of communication [13]. More generally speaking, humans and their behavioral patterns represent some form of baseline or in some cases ideal model for social robots. Since social robots are meant to support and interact with humans, ideally, they are also must incorporate a degree of comprehension for and adaptation to human behaviours and actions in such a way that allows for human intention to be analyzed and prepared for [14]. The ability for a technological system to understand parts of its environment and to then come up with predictions also connects to the idea of AI. Consequently, when human–robot interaction is supplemented by AI systems (such as IBM's Watson, which is presently used widely in medical fields, such as oncology [15]) we begin to see what is referred to as AI-enhanced social robotics.

When discussing AI in social robotics, one needs to clarify that here, too, the term AI is polysemous, hence carrying different meanings and understandings. The historical binary distinction of weak vs. strong AI [16] can also be described by rule-based vs machine learning-based algorithms [17]. Whereas in social robots both approaches exist, advances in artificial neural networks (ANN) and machine learning approaches are also gaining increasing attention [6, 18, 19]. The higher the expectations regarding seamless and natural communication of human end users with their social robots, the more the demand for AI-based social robot design. Kaplan [20] speaks of a machine learning approach wherein machine learning is required in instances of noisy data for more accurate sensory perception and data extraction. The 'learning' aspect is important, also in ANNs, since the artificial neural network is continuously "adjusting the weighted connections" in the network, so that the "system can be adjusted or 'tuned' to exhibit different kinds of output behavior" [17].

Despite being a prevalent term in both AI and robotics research across multiple fields, there is no concrete definition of AI-enhanced social robotics. Thus, for the purposes of this research, AI-enhanced social robotics will refer to any robot whose primary purpose falls within the mandate of social robotics and whose physical body is supported by software that incorporates AI in its interaction and communication methods. The emphasis on AI enhancement of communication methods is intentional as AI may be used to support robots that are not meant for interaction with humans and while these enhancements are integral to other aspects of robotics, they do not necessarily contribute to the robot's sociality.

1.2 Human–machine communication

In a nutshell, the field of Human–Machine Communication (HMC) focuses on communication *with* and not *through* machines, which might at first go contrary to our general conception of communication: "For many people, communication is understood as a process taking place between themselves and someone else. To communicate means posting to social media followers, texting a loved one, talking with a friend, giving a presentation to colleagues, or reading the latest news written by a journalist [21]. HMC, on the other hand, elevates the perceived notion of technology serving as some kind of 'medium' or channel between two human communication partners, and is thus defined as "the creation of meaning among humans and machines" [21] in which "technology is conceptualized as more than a channel or medium: it enters into the role of a communicator" [21, see also 22].

When it comes to social robots, communication between these machines and their human users has always taken a central role. As such, numerous HRI studies focus on communication [7, see also 23–26], and in many HRI interaction taxonomies, communication plays some form of a prominent role [see, for example, 27]. Zeller [6, 28] summarized these communication-focusing HRI studies into a taxonomy consisting of:

I. Text-based communication (e.g. user manuals or tablet/smart phone-based additional interaction modalities of robots)
II. Sound-based communication (e.g. basic signal sounds, pet sounds in pet robots, etc.)
III. Visual and non-verbal communication (e.g. colour-based signals, robotic gestures and movements, etc.)
IV. Speech-based communication (e.g. speech recognition and speech synthesis)

Given the aforementioned shift of perspective in social robotics from a techno-centric to an integrative socio-centric dimension, HMC clearly can serve as a guiding framework and approach. In fact, the field of social robots can be seen to represent a metaphorical double helix, with the techno-centric and socio-centric dimensions of social robots each representing one helix. [1] This double helix of social robots is also represented in the fact that they function as the object of studies in HRI as well as actual instruments or tools in HRI studies. For example, in a study that focused on the development of a social robot to support health care communication and aiming to initiate behavioral change, the social robot acted both as the tool to facilitate behaviour change in the users as well as the object of study for researchers seeking to improve the design of its personality [30]. In developing the communication patterns for the AI-enhanced social robot for health care, development of rapport was tested—evaluating both the robot as an object of study and as a tool for behaviour change and relationship building [30].

The double helix metaphor can be extended by using AI and the different algorithms executing AI-based behaviours as representing the connecting parts between the two helix strands. The concept of the backend and frontend in Human–Computer Interaction and HRI is well-known as, simply explained, the algorithms and generally software (backend) and the outward interaction and physical design (frontend) or 'what the end-user can see' [6]. In relation to this, the double helix would focus more on the AI aspect as the connecting concept and function between techno-centric or backend side and the socio-centric side [2] (see Fig. 1).

Shifting back to communication as a core aspect in HMC and HRI, we use an adaptation of Hall's [31] encoding and decoding model to apply the double helix concept to the creation of systems for robotic and AI technologies. In this model, the three following steps are relevant [32]:

(1) To stress the importance of the users' experiences, preconceptions, attitudes that can influence the human robot interaction or communication process;

[1] While some readers might find the usage of a metaphor rather unconventional, we are on the one hand paying tribute to the literary and philological 'backbone' of robots, given that the term 'robot' was coined in the fictional work of Čapek [29]. On the other hand, we are including here the shape of the helix as "a symbol of resilience", which includes the notion of resilience or persistence/perseverance found in technology with the fact that the helix shape is found throughout nature and in living organisms and thus merges the human and the technological dimension.

[2] It should be noted, though, that binary distinctions are always based on some form of reduction and generalization. Thus, any frontend design could, depending on the design approach, also have a strong techno-centric character when, for example, certain user-centric perspectives are missing. Therefore, the double helix metaphor is again a useful concept, given its intrinsic inter-changing nature.

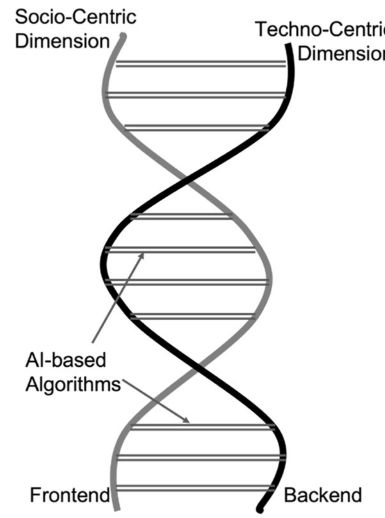

Fig. 1 Social robot double helix (author's own drawing)

(2) To show the different socio-cultural dimensions that influence the communication process, starting with the design of the robot;
(3) To apply Hall's notion of a circular process to interaction design, where the design of user interfaces, for example, consists of iterative design and development stages enriched by user feedback. (p. 15)

The model emphasises the role of the user in human–machine communication, acknowledging that the end user "brings their own experiences, knowledge, biases etc. to any human–robot interaction" [32]. With this, the model also integrates the socio-centric dimension in the design and development of techno-centric systems. The integrative approach must be seen as part of the end-user/robot interaction but also inherent in all the design stages of social robots: researchers involved in the development and design of social robots also bring their own 'epistemic cultures' (see below, sub-Sect. 2), which are rooted in certain conceptions and perceptions of the world—including, for example, the looks of social robots, haptics, functions, and likewise also of design of AI (referring back to the second point in the model above). The third point in the model introduces a pragmatic and applied solution for the integrative approach by suggesting a circular, iterative design model that—through different iterations of design-testing-feedback—offers the opportunity to consider both user and designer/developer expectations and experiences [32].

Consequently, this approach also corresponds with an HMC perspective, which ultimately puts human users at the centre of any research project while also allowing researchers to bridge the gap between traditional field-specific views and methods used in human–robot interaction (HRI), psychology, AI, and communication. For example, when considering HRI development, there are three predominant views that apply: robot-centred, robot cognition-centred, and human-centred [33]. By considering AI-enhanced social robotics from an HMC perspective, human users are placed at the centre with their interactions with both the physical robot frontend and an AI backend taken into consideration in the design process. Taking an HMC approach allows for interdisciplinary work, incorporating nominal quantitative data from surveys, for example, and psychological metrics with qualitative responses from interviews and user studies [34].

Arguably, it is the second factor of Zeller's [32] model that introduces the most prominent difficulty of doing research in HMC; showing "the different socio-cultural dimensions that influence the communication process, starting with the design of the robot" [32]. Experiences, preconceptions, and attitudes not only apply to users and their previous interactions with technology, but to the experts, researchers and designers who are behind the studies themselves. This adds a degree of complexity to the research as each researcher brings a different perspective, history, and goal to the project of robot development.

2 Addressing the challenges of collaboration

Varying research practices and metrics for success across the interdisciplinary field of AI research create challenges for collaboration. Field specific 'epistemic cultures' are defined as knowledge communities that run on expert processes and systems that create knowledge [35]. For each field of research, there is a set of actions, best practice methodologies, theoretical backgrounds, qualifications for evidence, ways to write, requirements for publication, and prerequisites for funding that make up the field's epistemic culture [35]. Each discipline has their own unique way to accumulate, validate and verify knowledge [see also 36]. By understanding how each field navigates their epistemic culture in relation to their surrounding fields, researchers can then understand the contribution of field-specific biases and their implications for the direction of research [35]. The notion of biases can be seen as strongly connected to the idea of epistemic virtues [37], which are internalised epistemic norms and values that guide researchers' approaches or interpretations [38]. Here lies the challenge of collaboration: field-specific metrics of success and internalised, non-validated norms and values towards the research material directly impact how research is planned, executed, and disseminated. The cultures of science, humanities, and engineering are each structurally integral to the frameworks of research and have implications for the ways in which research is conducted including publication venue (conference vs. journal publications), publication style (single vs. group author publications), levels of disclosure (open vs. confidentiality), and the funding model (internal grants vs. outside sponsors) [1, 39]. Metrics of success in each field represent different standards, despite all engaging with human interaction whether it be with a machine, other humans, or oneself. These factors play a role in choosing the methods that will be used and in selecting the appropriate theoretical drive; a well thought out research methodology with strong supporting methods and analysis plays a crucial role in how research is performed and the evaluation of its success.

2.1 Divisions of cognitive labor

Individual researchers' personalities, motivations, and their choices have considerable impacts on the direction of research and the epistemic culture of each field, which is referred to by Solomon [40] as the division of cognitive labor. The wider effect of this division can be seen when cognitive bias causes the distribution of cognitive effort to be skewed; for example, if a researcher is motivated by achieving publications in an attempt to further their career, they may choose to research areas that are more likely to help achieve those goals, rather than concentrating efforts on topics that are equally a worthy undertaking, albeit not a part of the dominant discourse or narrative [40]. Cognitive labor can be further divided when it comes to narrative shifts that bring an epistemic culture from dissent to consensus [41]. Debates in any field are integral to their progress and development; universal support is not necessarily normatively required, however, through this shift from dissent to consensus dominant narratives gain traction and meanings are solidified in scientific discourses [40]. This dissent is further compounded as it has been found that when members of minority groups voice disagreement with the majority, they often face discrimination for the remainder of the research collaboration [42].

Preconceptions, internal norms, and values define knowledge and research relies on checks and balances based on the reasoning of people in positions of power. In the epistemic cultures of the scientific community, various tactics are used to ensure that specific voices are prioritized, and the research is considered believable including fortification, positioning, stacking, staging, and framing, and captivating (controlling reader's position as an audience) [43]. This gives the collaborators who may not be based in a strictly scientific community three options for questioning or debating validity: give up, go along with the narrative, or work through each of the sources and references to find their origin [43]. The problem with the final option is the sheer volume of work needed to locate and engage with the origin sources. Due to the methods of stacking and fortification, scientific fact can be based on a single narrative that has been repeated and recycled for so long that it has completely erased the possibility for narratives other than the dominant to have an opportunity to be heard. It is here then, with the cyclical regurgitation of hegemonic values, that the division of cognitive labor appears most clearly. As was previously mentioned, consensus in a field is not always required nor found, as it is through dissent that progress is made. However, cognitive biases in research cause the distribution of effort to be skewed and require those in dissent against the dominant narrative to take on more of the cognitive labor [40].

2.2 Mixed method design

An approach that researchers can choose in interdisciplinary collaborative research is to employ mixed methods in the design of studies [44, 45]. Moreover, interdisciplinary fields can offer space for creative research methodologies that situate researchers between arts and science without devaluing the relationship to either [3, 44]. Creative research methodologies are broken down broadly into four key areas: arts-based research, research driven by technology, mixed methods research, and transformative research frameworks [3]. For the purposes of discussing how interdisciplinary collaboration informs AI and social robotics, the focus here is primarily on the creative methodology of mixed methods. Understanding methods, methodology, and theoretical drive allows for a critical and thorough examination of methods residing outside of the standardized practices of HRI. Here, methodology is defined as a conceptual framework while methods are considered as the tools used to gather and analyze data and present findings [3].

The design of mixed method research consists of core and supplemental components and a theoretical drive [46]. The design considers pacing, points of interface, and the inductive or deductive nature of the methods selected. The core component of mixed method projects is the primary method used; it is quantitative or qualitative in nature and must demonstrate enough rigor to be complete as a standalone study. The classification of *qualitative* versus *quantitative* research can be further broken down into data, tools/methods, design, epistemology, ontology, purpose, and the practical role of the research with each level of a mixed methodological project requiring quantitative and qualitative elements to some degree [47]. In the context of mixed method design the results and implications of the core component are bolstered by a supplemental component [46]. Subsequently, the supplemental component is selected strategically to either support or round out the core research method, allowing for a more holistic data set [46, 47].

Evaluations of AI-enhanced social robotic technology require researchers to study not only the frequency of interactions between robots and human users but also the *quality* of the interaction taking place [48]. Incorporating both analytical (robot evaluations that require little to no user involvement such as a heuristic evaluation or cognitive walkthrough) and empirical (user interaction-based research such as task efficiency and collaboration between user and robot) analysis can serve as an initial method for researchers to determine which tools will be best used for developing future evaluations [48]. While engineering-based practices often use more quantitative number-based methodologies, incorporating qualitative approaches such as ethnography can help to generate a more holistic understanding of the research at hand [49]. Mixed methods research demonstrates precisely how qualitative methods used in the social sciences and humanities can be leveraged to complement already relied upon quantitative methods of engineering and computer science without diminishing their importance in the AI research process [50].

Conducting AI and social robotics research using a mixed method design can provide this sought after robust and varying methodology, however, there are limitations [45, 50, 51]. Applying for funding is already complicated by interdisciplinarity and adding in a mixed methods framework requires researchers to further explain and detail the reasoning to agencies that may be familiar with either qualitative or quantitative methods [39, 45]. Sample size requirements for achieving validity in quantitative and qualitative research vary greatly, with quantitative research often requiring exponentially more data to achieve statistically significant results [1]. Problems arise, particularly in validity, when limited methods for researching interaction are used, including, but not limited to lack of significant sample sizes for participant pools that are representative of the humans the robots are being designed to interact with, and a lack of convergent validity [4]. Common methods of assessment in social robotics include self-assessments tools, behavioral observations, psychophysiological measures, interviews, and task performance, however, these methods of assessment are not standardized across all fields [4, 51]. Self-assessment tools, such as surveys and questionnaires allow the participants to detail their experience. They can be problematic since they open the possibility for participants to respond how they believe the researchers want them to, or how they believe a good participant should respond, thus clouding the data [4, 52]. Quantifying behavioral observations involves researchers observing as the human participant interacts with the robot, taking note of the various modes of interaction and gaining information about the interactions themselves [4, 53]. Reliable observations require that researchers consider the function, causation, development, and evolutionary history of the behaviours they are observing—however achieving this is arguably almost impossible. Instead, using a framework that further incorporates classifying data can allow for fewer potential errors in validity [53]: interviews are flexible in that the degree of structure can be modified to fit the study at hand, they allow for greater and more detailed responses from participants and can lead to rich datasets and qualitative analysis particularly when they are supplemented with behavioural observations as noted above [4, 53]. This does not mean they are flawless, however, as participants can use response acquiescence or deviation, as well as social desirability to unintentionally skew results [4]. Finally, empirical analysis-based task performance metrics can be used to see how well the human and robot are able to work together to perform a task or complete an interaction as smoothly as possible [4, 48]. This can be measured in ways such as noting time spent completing the task or the number of human or robot errors, producing a quantifiable result that can then be supported by qualitative interviews or focus groups [4]. Other factors affecting the results and validity of HRI research can include study location and environment, type and number of robots, other equipment involved (and its complexity of use), contingencies for potential equipment failures, the detail of the study protocol, the methods for recruitment of representative subjects, and the ethical considerations of the study [4].

The mixed methods methodological approach also allows for a consistent HMC implementation. By addressing the interaction between AI-enhanced social robots and humans as communication between these two actors, we need to see both actors as core components rather than one as core components and the other as supplemental. Instead, the supplemental components are here represented as the aforementioned factors such as study location and environment, user experience and expectations, etc. While having two core components sounds challenging, the mixed methods framework allows one to assess and measure each with their own instrument—either qualitative or quantitative. Bringing this back to the idea of the double helix, the mixed methods idea, based on interdisciplinary collaborations, can then also integrate the different epistemic cultures, which are expressed by the different methods used. At the same time, given the double helix, we find that both sides—science/engineering-based research and humanities/social sciences research—are integrated as equal contributors for the two core components. The supplemental factors, then, can be used to enhance and enrich the results from the core components.

3 Collaboration in practice: health care applications

Artificially Intelligent technology has transformed the decision-making process for health care clinicians and offers new possibilities for health care communication with patients. A timely and challenging objective for clinicians is the use of information technology for patient education while ensuring high quality care and safety. Following the above discussion ethical and practical challenges associated with interdisciplinary collaborative research on AI-enhanced social robotic systems we introduce a health care application for which a human–machine communication framework may be applied. The following examines and applies Zeller's [32] human–machine communication framework and double helix model to the early findings of a study in which researchers are concentrated on developing an AI-enhanced social robot to leverage health and risk communication techniques for skin cancer prevention [30]. These preliminary results are part of a larger study with aims to position an AI-enhanced social robot in dermatology clinics to discuss skin cancer prevention methods with patients as a method of encouraging behaviour change techniques [30]. By considering this AI-enhanced social robot through a HMC lens researchers can better examine the possibilities for collaboration and knowledge building across disciplinary boundaries.

3.1 Robot-facilitated behaviour change

Beginning with the socio-centric strand of the double helix we consider the notion of behaviour change interventions and their external challenges. The motivation to change may be the most important target for health change interventions; many individuals have very low motivation to adopt positive health change behaviours and are therefore very resistant to making these changes for a variety of reasons, including low confidence, perceived barriers, and low outcome expectancies [54]. Interventions that address these factors and increase motivation to adopt healthy behaviours may lead to long-lasting change. Equally importantly, the motivation to change must be followed by putting into place a plan of action, and long-term formation of healthy habits that develop individual health awareness. The second, techno-centric strand of the double helix model comes into play with the technologies developed for individual health awareness, such as the introduction of wearable devices and health monitoring mobile applications [55]. This technology is part of a movement referred to as the "quantified self" [56]. The notion is that the increase of health care information recording, and reporting can educate and motivate individuals to develop and adopt better habits for improved health. The technologies currently used as a part of the quantified self are most often characterized by their immediate availability and ease of access, for example, fitness watches and their associated mobile applications are designed to be always within reach for the user. An AI-enhanced social robot [3] placed in a dermatology clinic or other health care setting differs from these technologies in its access being limited to the interactions at physical locations. As such researchers proposed a mobile application to pair with the robot so that the experience could continue beyond the physical space [30].

Designing an AI-enhanced social robot with the intention of assisting with behaviour change requires that a relationship of rapport be built between the user and the robot. Nomura and Kanda [57] stress the importance of rapport building between social robots and humans with their development of the Rapport-Expectation with a Robot Scale (RERS). In their experiment Nomura and Kanda [57] found that robots demonstrating relational behaviour (asking the user what tasks needed to be completed and treating the user as a colleague throughout the tasks) improved the rapport-expectations of the user. The scale developed by Nomura and Kanda [57] which includes questions such as "This robot may understand

[3] Softbank's Pepper robot was used for the purposes of this study. Pepper stands approximately 1.2 m (4ft) high with humanoid upper body features, wheels for movement, and a tablet on its chest. Note that the tablet was not used during the user studies.

me" and "This robot could devote itself to me" (answered on a seven- choice scale) may be considered for future user testing of my anxiety-managing robot (p 24). Following the concept of imitation as a rapport building exercise, Riek, Paul, and Robinson [58] used variations in robot facial expressions to determine if the degree of mimicking influenced perceived interactional satisfaction. Riek et al. [58] based their findings on a combination of gestural analysis and self-report questionnaires. Participants' responses often echoed the same concept – the robot was not believable [58]. From the robot's mechanical movements to its difficult-to-understand responses the results of this study emphasized the importance of more fluid movements and responses for future robots.

3.2 User studies

The early stages of research to be examined include two sets of user studies completed through an iterative process: the first tested various personalities of the robot to determine which was preferred by the users while the second implemented an adjusted personality script and a complementary prototype mobile application [30]. The first round of user studies is broken down into two phases: 'personality' and 'brain'. In phase 1, the 'personality' script users answer a series of open-ended questions about their life (such as their work and hobbies) before Pepper guides the conversation to the topic of sunscreen use. In developing the communication patterns for the AI-enhanced social robot for health care, development of rapport is tested through a variation of personalities and gestures. Pepper then asks questions about the user's general experiences with sunburn and their use of sunscreen. Phase 2, the 'brain' script, begins with Pepper addressing the user by their given name which is retrieved from the first phase. In this stage Pepper quizzes the user on their sunscreen knowledge through a combination of multiple choice and open-ended questions, providing answers and facts after each user response [30].

Inductive analysis of the six participant's interactions and debrief responses revealed five themes: positive interactions, negative interactions, tailoring responses (researcher noted or self-declared from users), 'personality' vs 'brain' interaction comparison, and gestures [30]. Negative interactions were classified as any interaction that resulted in a conversational inconsistency or interruption of the flow of the interaction, as well as any user reported issues with specific interactions. Conversational inconsistencies were further broken down into misinterpretations, Pepper errors, interruptions, and user error. One notable result of the study was the users' tailoring of responses to fit the interaction with Pepper [30]. While four of six participants enjoyed the ice breaking questions that Pepper used during the 'personality' stage of the study, two participants noted that they preferred the 'brain' or quiz section as it felt more appropriate for the interaction with a robot [30]. Most users noted again their enjoyment of the personalization and continuity between studies when Pepper called them by name. All participants felt comfortable being taught and quizzed on information by Pepper and none questioned or argued the information that Pepper provided them.

The second set of user studies features a revised script and gesture modification that took the pieces that were most well received from both the 'personality' and 'brain' scripts and introduces an early prototype of the mobile application that would be paired with the Pepper robot experience. The mobile application prototype consists of the following features: log for daily sun exposure, log for sunscreen use, quiz for learning about sunscreen and protection, information pages, schedule for sunscreen with alarm [30]. The study found that the robot had trouble with accents, an issue that contributed to misinterpretation and tailoring of responses however, the robot was still perceived as being happy, compassionate, and non-threatening [30]. The prototype mobile application, while having useful features according to participants, did not meet user expectations after their interaction with a much more visually advanced social robot.

3.3 Challenges, opportunities, and barriers to adoption

The above early-stage user studies demonstrate the distinct challenges to the adoption of AI-enhanced social robotics. Trouble with communication, as highlighted in the robot's difficultly with maintain flow without interrupting as well as understanding various accents and struggles with misinterpretation lead to tailoring of responses on the part of users. This disconnect in communication is something that can be addressed by experts in AI and applied using AI-based algorithms that address expectations of users and their preconceived notions of robots in the interactions themselves. Researchers going forward could implement a circular process of interaction design in which these algorithms are added and tested through both quantitative and qualitative measures such as the previous iterative user studies as well as focus groups, field testing, and simulation testing as is presently used in engineering, health, and communication studies.

4 Applying collaborative solutions

The design of AI-enhanced robots is evolving quickly, and with it come new metrics for social robot development and evaluation. Artificial intelligence as a field has experienced several growth winters; interdisciplinary and collaborative perspectives are one route forward that researchers can take to address these lulls [59] For this evolution to proceed ethically, it must be done from a position that is user-centred and interdisciplinary [60, 61]. The design of technology is inherently imbedded with assumptions about its use [60]. When technology is designed with user input at every stage (such as when using an HMC framework) the space between research intention and user experience narrows. User-centred methodologies implemented with communication research methods allow design to go beyond preconceived notions of user needs to address the issues of race, gender, disability, and privilege as integral factors in the conceptualization of new technologies [62–65].

Key suggestions from our discussion of collaborative solutions to current interdisciplinary challenges in AI and robotics are as follows:

1. Diversify the data (and the analysis): taking a mixed-methodological approach to the evaluation of AI-enhanced robotics allows researchers to bring methods from multiple disciplines to collaborative research, forming a more holistic picture of the research,
2. Discuss epistemic values in interdisciplinary teams: when working with teams from disciplines with differing outputs such as publication and conference venues, having preliminary discussion on expected outcomes can help structure workflow from the beginning,
3. Collaboration works best when it is incorporated at every stage of research: taking a position of collaboration rather than a division of labor allows researchers to make the most of interdisciplinary approaches.
4. Have continuous discussions around different notions and perceptions regarding ethics and academic integrity in interdisciplinary teams. Often, these different notions and guidelines need to be discussed and solutions found.

Applying an HMC approach to the problem of collaboration in AI and social robotics allows researchers to incorporate a diversity of methods, approaches, and desired deliverables in their work. By taking a mixed methodological perspective researchers can emphasise the experience that users bring to and receive from interactions with social robots. This allows researchers to still incorporate the quantitative aspects of user interface design when working with qualitative research [32]. Circular processes of interaction design as mentioned in Zeller's [32] model for HMC allow for a multitude of methods and approaches to be applied, addressing the challenges of equal participation and contribution to collaboration [44, 45, 47]. By acknowledging the positionality of each field in the research process and providing opportunities for meaningful contribution through a combination of methods, divisions of cognitive labor shift from divisive to diversifying.

Developing a robust and varying methodology worthy of an interdisciplinary field such as AI-enhanced social robotics is a daunting task. In taking an HMC approach researchers give value to traditional communication and HRI research while emphasising the importance of human-centered methods and acknowledging the need to address researchers' and field-based epistemic cultures. Through understanding the pitfalls and limitations of research methods it is possible to devise stronger strategies for future projects, leading to more valid conclusions and building a foundation for a stronger future for the field. The methods for designing and testing AI-enhanced social robots are each partially flawed. However, when used in combination with methods from other fields, researchers can demonstrate convergent validity and bolster results, indicating correlation (or deviation) between the various methods and offering a more robust response. The challenges faced by researchers in the interdisciplinary fields of research demonstrate precisely how leveraging supplementary methods leads to better performances in AI-enhanced human–robot interaction. This is not to say that collaboration is impossible; interdisciplinarity offers the opportunity to create a shared language across disciplines and leverage the methodologies from a variety of fields to generate holistic research plans [44]. Individual and field-specific biases may hinder a potential collaboration but may also allow for new perspectives on existing problems in alternate fields of study.

Acknowledgements Toronto Metropolitan University announced in August 2021 that it would change its name after protests that linked its namesake, 19-century educational reformer Egerton Ryerson, with the design of the residential-school system in Canada.

Author contributions Authors FZ and LD both made substantial contributions to the conception or design of the work, drafted the work and revised it critically for important intellectual content; approved the version to be published; and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. Both authors read and approved the final manuscript.

Funding The Creative School, Toronto Metropolitan University.

Data availability Not applicable.

Code availability Not applicable.

Declarations

Competing interests The authors declare no competing interests.

References

1. Lazar J, Feng JH, Hochheiser H. Research methods in human-computer interaction. San Francisco: Elsevier Science & Technology; 2017.
2. Domino SE, Smith YR, Johnson TRB. Opportunities and challenges of interdisciplinary research career development: implementation of a women's health research training program. J Womens Health. 2007;16(2):256–61. https://doi.org/10.1089/jwh.2006.0129.
3. Kara H, Gergen KJ, Gergen MM. Creative research methods in the social sciences: a practical guide. Policy press. 2015.
4. Bethel CL, Murphy RR. Review of human studies methods in HRI and recommendations. Int J Soc Robot. 2010;2(4):347–59. https://doi.org/10.1007/s12369-010-0064-9.
5. Dautenhahn K. Socially intelligent robots: dimensions of human-robot interaction. Philos Trans Royal Soc B. 2007;362(1480):679–704. https://doi.org/10.1098/rstb.2006.2004.
6. Zeller F. Algorithmic machines: from binary communication designs to human-robot interactions. In: Taddicken M, Schumann C (Eds). Algorithms and Communication; 2021. p. 95–133.
7. Breazeal C, Dautenhahn K, Kanda T. Social Robotics. In: Springer Handbook of Robotics; 2016. p. 1935–1972. https://doi.org/10.1007/978-3-319-32552-1_72
8. Calzado J, Lindsay A, Chen C, Samuels G, Olszewska JI. SAMI: interactive, Multi-Sense Robot Architecture. In: 2018 IEEE 22nd International Conference on Intelligent Engineering Systems (INES). 2018. p. 000317–000322. https://doi.org/10.1109/INES.2018.8523933
9. Giger JC, Piçarra N, Alves-Oliveira P, Oliveira R, Arriaga P. Humanization of robots: is it really such a good idea? Hum Behav Emerg Technol. 2019;1(2):111–23. https://doi.org/10.1002/hbe2.147.
10. Blow M, Dautenhahn K, Appleby A, Nehaniv CL, Lee DC. Perception of robot smiles and dimensions for human-robot interaction design. In: ROMAN 2006—The 15th IEEE International Symposium on Robot and Human Interactive Communication. 2006; 469–474. https://doi.org/10.1109/ROMAN.2006.314372
11. Breazeal C. Toward sociable robots. Robot Auton Syst. 2003;42(3–4):167–75. https://doi.org/10.1016/S0921-8890(02)00373-1.
12. Tapus A, Mataric M, Scassellati B. Socially assistive robotics [Grand Challenges of Robotics]. Robot Autom Mag, IEEE. 2007;14:35–42. https://doi.org/10.1109/MRA.2007.339605.
13. Deng E, Mutlu B, Mataric M. Embodiment in socially interactive robots. FNT in Robot. 2019;7(4):251–356. https://doi.org/10.1561/2300000056.
14. Ji Y, Yang Y, Shen F, Shen HT, Li X. A survey of human action analysis in HRI applications. IEEE Trans Circuits Syst Video Technol. 2020;30(7):2114–28. https://doi.org/10.1109/TCSVT.2019.2912988.
15 Yoon SN, Lee D. Artificial intelligence and robots in healthcare: what are the success factors for technology-based service encounters? Null. 2019;12(3):218–25. https://doi.org/10.1080/20479700.2018.1498220.
16. Dreyfus HL, Dreyfus SE. Making a mind versus modeling the brain: artificial intelligence back at a branchpoint. Daedalus. 1988;117(1):15–43.
17. Gunkel DJ. An introduction to communication and artificial intelligence 1st edition. Polity. 2020.
18. Bartneck C, Belpaeme T, Eyssel F, Kanda T, Keijsers M, Šabanović S. Human-Robot interaction: an introduction 1st edition. Cambridge University Press. 2020.
19. Müller C. Market for professional and domestic service robots booms in 2018. IFR secretariat blog. 2019.
20 Kaplan J. Artificial intelligence: what everyone needs to know. Oxford: Oxford University Press; 2016.
21. Guzman AL. Human-machine communication: rethinking communication, technology, and ourselves. Incorporated: Peter Lang Publishing; 2018.
22. Guzman AL, Lewis SC. Artificial intelligence and communication: a human-machine communication research agenda. New Media Soc. 2020;22(1):70–86. https://doi.org/10.1177/1461444819858691.
23. Onnasch L, Roesler E. A taxonomy to structure and analyze human-robot interaction. Int J of Soc Robotics. 2021;13(4):833–49. https://doi.org/10.1007/s12369-020-00666-5.
24. Baron NS. Shall we talk? Conversing with humans and robots. Inf Soc. 2015;31(3):257–64. https://doi.org/10.1080/01972243.2015.1020211.
25. Sandry E. Robots and communication. Springer. 2015.

26. Taipale S, Leopoldina F. Communicating with machines: robots as the next new media. In: Guzman AL. Human-machine communication: rethinking communication, technology, and ourselves. Peter Lang Publishing, Incorporated; 2018.
27. Thomaz A, Hoffman G, Cakmak M. Computational human-robot interaction. ROB. 2016;4(2–3):105–223. https://doi.org/10.1561/2300000049.
28. Zeller F. Mensch-roboter interaktion: eine sprachwissenschaftliche perspektive. Press: Kassel Univ; 2005.
29. Čapek KRUR. Rossum's universal robots.1921:101.
30. Dwyer L, Zeller F, Smith D, Lima H. Communication leveraging social robots for healthcare paper presented at congress 2021 meeting of the Canadian communication association. 2021.
31. Hall S. Culture, community, nation. Cult Stud. 1993;7(3):349–63. https://doi.org/10.1080/09502389300490251.
32. Zeller F. New research avenues in human robot interaction. In: Zhang D, Wei B. Human–robot interaction: control, analysis, and design. Cambridge scholars publishing. 2020.
33. Prati E, Peruzzini M, Pellicciari M, Raffaeli R. How to include user eXperience in the design of human-robot interaction. Robot Computer-Integr Manuf. 2021;68:102072. https://doi.org/10.1016/j.rcim.2020.102072.
34. Speicher M. What is usability? A characterization based on ISO 9241–11 and ISO/IEC 25010. arXiv:150206792 [cs]. http://arxiv.org/abs/1502.06792. Accessed 9 Jan 2019.
35. Cetina KK. Epistemic cultures: how the sciences make knowledge 1 edition. Harvard University Press. 1999.
36. Snow CP. The two cultures. Cambridge University Press; 1998. http://hdl.handle.net/2027/heb.03176. Accessed 10 Feb 2022.
37. Daston L, Galison P. Objectivity. New York: Zone Books; 2007.
38. Stevens M, Wehrens R, de Bont A. Epistemic virtues and data-driven dreams: on sameness and difference in the epistemic cultures of data science and psychiatry. Soc Sci Med. 2020;258:113116. https://doi.org/10.1016/j.socscimed.2020.113116.
39. Dahlberg B, Wittink MN, Gallo JJ. Funding and publishing integrated studies: writing effective mixed methods manuscripts and grant proposals. In: SAGE handbook of mixed methods in social & behavioral research. SAGE Publications, Inc; 2010:775–802. https://doi.org/10.4135/9781506335193.n30
40. Solomon M. Social empiricism. MIT, Press; 2007.
41. Levy N, Alfano M. Knowledge from vice: deeply social epistemology. Mind. 2020;129(515):887–915. https://doi.org/10.1093/mind/fzz017.
42. Rubin H, O'Connor C. Discrimination and collaboration in science. Philos Sci. 2018;85(3):380–402. https://doi.org/10.1086/697744.
43. Latour B. Science in action: how to follow scientists and engineers through society. Harvard University Press. 1987.
44. Moirano R, Sánchez MA, Štěpánek L. Creative interdisciplinary collaboration: a systematic literature review. Think Skills Creat. 2020;35:100626. https://doi.org/10.1016/j.tsc.2019.100626.
45. Teddlie C, Tashakkori A. Overview of contemporary issues in mixed methods research. In: SAGE handbook of mixed methods in social & behavioral research. SAGE Publications, Inc; 2010:1–42. https://doi.org/10.4135/9781506335193.n1
46. Morse JM, Niehaus L. Mixed method design: principles and procedures. Left Coast Press. 2009.
47. Biesta G. Pragmatism and the philosophical foundations of mixed methods research1. In: SAGE handbook of mixed methods in social & behavioral research. SAGE Publications, Inc; 2010:95–118. https://doi.org/10.4135/9781506335193.n4
48. Lindblom J, Alenljung B, Billing E. Evaluating the user experience of human-robot interaction. InHuman-Robot Interact. 2020. https://doi.org/10.1007/978-3-030-42307-0_9.
49. Jacobs A, Elprama S, Jewell CIC. Evaluating human-robot interaction with ethnography. InHuman-Robot Interact. 2020. https://doi.org/10.1007/978-3-030-42307-0_11.
50 Damholdt M, Vestergaard C, Seibt J. Testing for 'Anthropomorphization': a case for mixed methods in human-robot interaction. InHuman-Robot Interact. 2020. https://doi.org/10.1007/978-3-030-42307-0_8.
51 Werner F. A survey on current practices in user evaluation of companion robots. InHuman-Robot Interact. 2020. https://doi.org/10.1007/978-3-030-42307-0_3.
52. Bethel CL, Henkel Z, Baugus K. Conducting studies in human-robot interaction. InHuman-Robot Interact. 2020. https://doi.org/10.1007/978-3-030-42307-0_4.
53. Grandgeorge M. Evaluating human-robot interaction with Ethology. InHuman-Robot Interact. 2020. https://doi.org/10.1007/978-3-030-42307-0_10.
54. Hardcastle SJ, Hancox J, Hattar A, Maxwell-Smith C, Thøgersen-Ntoumani C, Hagger MS. Motivating the unmotivated: how can health behavior be changed in those unwilling to change? Frontiers in Psychology. 2015. https://www.frontiersin.org/article/https://doi.org/10.3389/fpsyg.2015.00835. Accessed 15 Apr 2022.
55 Parmanto B, Pramana G, Yu DX, Fairman AD, Dicianno BE. Development of mHealth system for supporting self-management and remote consultation of skincare. BMC Med Inform Decis Mak. 2015. https://doi.org/10.1186/s12911-015-0237-4.
56. Swan M. The quantified self: fundamental disruption in big data science and biological discovery. Big Data. 2013;1(2):85–99. https://doi.org/10.1089/big.2012.0002.
57. Nomura T, Kanda T. Rapport-expectation with a robot scale. Int J of Soc Robot. 2016;8(1):21–30. https://doi.org/10.1007/s12369-015-0293-z.
58. Riek L, Rabinowitch TC, Bremner P, Pipe A, Fraser M, Robinson P. Cooperative gestures: effective signaling for humanoid robots. 2010;61–68. https://doi.org/10.1109/HRI.2010.5453266
59. Jiang Y, Li X, Luo H, Yin S, Kaynak O. Quo vadis artificial intelligence? Discov Artif Intell. 2022;2(1):4. https://doi.org/10.1007/s44163-022-00022-8.
60. Carroll JM, Kellogg WA. Artifact as theory-nexus: hermeneutics meets theory-based design. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. CHI '89. Association for Computing Machinery. 1989:7–14. https://doi.org/10.1145/67449.67452
61. Carroll JM, Rosson MB. Participatory design in community informatics. Des Stud. 2007;28(3):243–61. https://doi.org/10.1016/j.destud.2007.02.007.
62 Bauer GR. Incorporating intersectionality theory into population health research methodology: challenges and the potential to advance health equity. Soc Sci Med. 2014;110:10–7. https://doi.org/10.1016/j.socscimed.2014.03.022.

63. Boyles C. Counting the costs: funding feminism in the digital humanities. In: Losh E, Wernimont J, editors. Bodies of information intersectional feminism and the digital humanities. Minneapolis: University of Minnesota Press; 2018. p. 93–107. https://doi.org/10.5749/j.ctv9hj9r9.10.
64. Silva S, Kenney M. Algorithms, platforms, and ethnic bias: an integrative essay. Phylon. 2018;55(1 & 2):9–37.
65. Tenenbaum C. Not intelligent: encoding gender bias. Minn J Law Sci Technol. 2020;21:15.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.