Editorial
Special Issue Interaction With Artificial Intelligence Systems: New Human-Centered Perspectives and Challenges

I. Introduction

Artificial intelligence (AI) methods are being applied to numerous areas, including medicine, security, transportation, industry, smart homes and cities, business, social sciences, and psychology. AI is currently a part of our daily lives. People interact continuously with AI: it is inside houses, computers, mobile phones, and applications. AI can make predictions and give suggestions for movies, songs, or future purchases based on our previous choices. It affects the society and economy. People are fascinated by AI in the ways it improves and facilitates human life (improving health care and discharging workers from heavy or dangerous jobs). People are also concerned with AI's implementation risks, such as ethical, security, and privacy issues. There are also concerns that AI machines may replace humans in various activities. AI researchers and practitioners have been facing these issues and further research is needed to design technical and regulatory applicable solutions.

This special issue (SI) investigates a broad range of issues deriving from human interaction with AI. We encouraged interdisciplinary and multidisciplinary contributions toward understanding how AI could improve human life in various fields. Specifically, the contributions in this SI aim to improve the quality of the interaction between humans and AI systems and investigate new solutions to improve user trust in AI in a broad range of domains (medicine, psychology, education, security, transport, social networks, smart home devices, work, and recommendations).

One of the main ways to build trust in AI is to make its outputs transparent and interpretable by humans (producing model-specific intrinsic explanations for transparent white-box models or post-hoc explanations for black-box models). Although the issues of transparency and explainability in AI have been long recognized, they emerged as a research field only recently to explain the decisions of deep neural networks that offer practical solutions to many contemporary problems. Explainable AI models are extremely important in all cases where AI systems are required to make decisions that impact a person's life or where AI systems are (or will likely be) an aid to human decision making such as in healthcare applications, education, finance, and social science.

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Possible presence of bias in a system's output is another issue that arises when AI systems are required to make decisions that may impact a person's life. As known in the social sciences, human decisions are inherently biased. This bias may translate to the data used to train AI systems that may become biased. Fairness in AI is an emerging research field that aims at training fair predictive models from possibly biased data.

II. Contributions I

The contributions in this SI are described and grouped by major topics.

A. Natural Human–Robot Interaction and Applications

There is a natural expectation that robots have AI, and the expectations are often too high: the robot is expected to speak, respond socially, and perform useful supportive tasks for humans. The current research attempts to design natural human–robot interactions and identify potentially useful applications. Several studies featured in this SI reflect various aspects of these developments. In [A1], Zhao *et al.* investigate how robots can facilitate and enhance the human–human interaction in the case where one of the communicating partners is affected by dementia (a condition that makes a person forget events, names, and make everyday communication a challenge). Persons with dementia will have progressive communication difficulties, leading to increased social isolation and negative emotions. The paper by Zhao *et al.* explored the feasibility of using social robots as personal memory assistants, thus improving the perceived communication quality between people with dementia and their friends, relatives, and caregivers. The robot stores personal information for older patients and, when touched, assists in their communication through voice and screen display of events and people. The results revealed that by providing memory support, the robot significantly improved the perceptions of the perceived communication ability and performance of patients with dementia and improved their personal image. The willingness of others to communicate with the patient increased.

In [A2], Medeiros *et al.* focus on the possibility that chatbots provide social support through an online platform. The "computer-generated emotional support" concept (CGES) appeared recently in the literature. The outputs of the CGES machines are supportive messages that are similar to those that humans would generate, leading the concept of online social support to be more than only a possibility [1]. The authors implemented a chatbot that able to give support to users suffering from stress in the form of short dialogues. The main goals of the study were to understand if the bot was effective in ameliorating the self-reported stress of the participants and to gain an insight into the influence of being aware of interacting with AI (rather than a human being). The authors concluded by confirming prior research observations that artificially generated emotional support is effective in ameliorating stress levels. Nevertheless, virtual agents still fail to simulate a degree of empathy comparable to humans. That would explain why the participants had better outcomes when they were aware of interacting with another human.

In [A3], Cai *et al.* investigate the dialogue-based conversational recommender systems as an agent that supports users to communicate with the system in natural language to facilitate feedback provision and product exploration. Similarly, as Zhao *et al.*, they empirically study user perception and interaction with humans. The contribution by Cai *et al.* especially focuses on finding out how to best support users in providing feedback on the received recommendation. The authors aim to develop effective critiquing mechanisms for dialogue-based conversational recommender systems to improve their feedback elicitation process (allowing users to critique the current recommendation during the dialogue). Three prototype systems that apply different critiquing techniques in two typical recommendation tasks (basic recommendation and exploration oriented) were implemented. The authors show that the second task simulates more user interaction while the basic recommendation task results in a higher user satisfaction. Moreover, when users perform an exploration-oriented task, the type of critiquing techniques is more likely to influence user perception and moderate the relationships between certain interaction metrics and users' perceived serendipity.

The perception of the physical interaction between robots and humans is an exciting trend in the ongoing quest to understand and properly support humans. In [A4], Hu *et al.* consider that unanticipated physical actions by the robot will be inevitable with the deployment of robots in human-populated environments. The perception and understanding of intentionality of such actions call for novel control architectures that will consider how the robot should execute such actions in a physically and psychologically safe manner. The paper by Hu *et al.* attempts to quantify the humans' physical and mental state during a game-based interaction with a robot. The authors collect behavioral and physiological data from humans during this interaction. The data analysis showed the relationships between participants' physical and physiological data and their age, gender, perception, and personalities. The future direction is to develop a new generation of transparent AI systems that can naturally and intuitively interact with humans in physical environments. In [A5], Wolfert *et al.* attempt to create a common standard in gesture generating systems. The authors attempted to formalize and standardize the design of cospeech gesturing. Cospeech gestures for robots or screen-based embodied conversational agents may be created using rule-based or data-driven models. The latter is gaining traction because of the increasing interest from the applied machine learning (ML) community. A systematic review of cospeech gesture generation methods for iconic, metaphoric, deictic, and beat gestures is presented. The evaluation methods for the generation of these classes of gestures are reviewed to conclude that the field requires more rigorous and uniform tools for cospeech gesture evaluation. The authors offered recommendations and standards for empirical evaluation to help systematically test generative models across studies.

Another aspect crucial in the "human-intelligent machine" relationship relates to emotions. The way people interpret artificially produced emotions plays a major role in the quality of the interaction with machines and contributes to the level of trust. Indeed, emotions play a key role in our life. In [A6], Amorese *et al.* studied the differences between the emotional experience induced by a human being and the experience induced by a virtual agent. Previous findings have shown mixed results: it is not clear if the interpretation of emotion changes depending on who has elicited it (another human being or a virtual agent). The authors showed that age and gender need to be considered as variables affecting the AI emotions' interpretation. Nevertheless, even the age and gender of the faces used as stimuli have a strong influence. Younger experimental subjects have been shown to better recognize expressions of anger, sadness, and neutrality. However, female participants had better performances in recognizing expressions of sadness, fear, and neutrality. Moreover, it was surprising that expressions of happiness, surprise, and neutrality were easily and better identified when elicited by virtual agents. Instead, sadness and fear were better recognized when expressed by a human face. The age of the faces used as stimulus resulted in influencing the recognition performance. For example, anger and surprise emotions show a more efficient recognition when the emotion is provided by a young face.

In [A7], Beraldo *et al.* explored the fascinating topic of having a shared intelligence between a human and a machine. The authors propose a shared intelligence system for brain–machine interface teleoperated mobile robots where the user's intention and the robot's intelligence are equally participating in the decision process. A system that relies on policies guides the robot's behavior. The fusion of these policies is expected to lead to the identification of the next, most logical for the user, location of the robot. The experimental results showed that a shared intelligence system allows users to efficiently teleoperate the robot and ensure a level of BMI navigation performance comparable to the keyboard control. It also actively assisted BMI users in accomplishing the desired tasks.

In [A8], Gottardi *et al.* address the problem of shared control in robot teleoperation. The aim is to let users focus on high-level goals, while robotic intelligence may take care of low-level control problems, such as safe motion that is adjusting the robot's trajectory to avoid collisions with obstacles that may cause damage to the robot itself or its surroundings. The authors propose a framework for real-time shared control teleoperation that integrates user intention prediction with collision avoidance based on an improved artificial potential field method that dynamically generates escape points around obstacles. The framework is quite general, being compatible with both mobile and manipulator robots in static and dynamic environments.

B. Natural Human–Machine Interaction

A core part of the interaction between humans and intelligent machines is the capability of AI systems to interpret human communication. Impressive results have been achieved in the last few years in the field of natural language processing [2] and in spoken language understanding [3]. However, humans communicate in numerous different ways, not only through language but also with body gestures.

In some cases, the interpretation of body gestures is of utmost importance, such as in self-driving cars where autonomous driving systems should be able to interpret traffic command gestures of police officers.

In [A9], Wang *et al.* address the problem of recognizing traffic command gestures. This is a core task for driver assistance or autonomous driving, where high accuracy, quick response time, and a low computational cost are essential requisites. The authors propose an ML model based on handcrafted features and an LSTM network. Experiments are performed using a public domain dataset (Chinese traffic police gesture). Field tests were conducted, showing and analyzing the gap between results using benchmark datasets and the practical application of ML methods.

The problem of interpreting human movements becomes even more challenging when multiple humans are interacting with each other. However, the ability to recognize such interactions will be a key component of every machine that aims to naturally interact with humans.

In [A10], Haroon *et al.* address the problem recognizing human interaction using deep neural networks. The proposed architecture exploits skeleton-based features that provide a high-level representation of the core points of the human body. Such points may be predicted from a video stream without requiring any dedicated hardware. The architecture employs bidirectional LSTM and 3D-CNN. Considered are both short-term and long-term dependencies among spatial and temporal features. The authors show that the proposed architecture improves the state-of-the-art results in two benchmark datasets.

C. AI as Support of Human Intelligence and Creativity

When considering the human interaction with AI systems, a broad range of novel possibilities and challenges arise. The interaction with humans may allow the exploration of AI in applications where AI systems alone cannot be applied. For instance, AI systems have long been considered inadequate in activities involving creativity. Recently, this trend began to change with deep learning systems being able to produce images and music [4], [5]. Moreover, it has been shown that it is possible to learn the style of an artist and to generate new compositions following the same style [6].

In [A11], Zhou *et al.* propose a tool to assist designers to incorporate foreign cultural elements in their products. A deep-learning-based style transfer technique is introduced to automatically produce a design image of the same content as the uploaded design content image. It also preserves the cultural style of the selected style image.

The proposed AI-based tools have been shown to effectively increase designers' cultural awareness in respect of four cultural element dimensions (color, material, pattern, and form) and be a valuable support to human designers.

In many practical scenarios, the user interactions with ML systems provide information that may be used as training data for the learning algorithm. In this setting, the user and the machine are collaborating to solve a task. However, it is often unreasonable to assume that users to be familiar with the dynamics of the adopted ML/AI algorithms. Thus, the cooperation between users and machines should be both effective and intuitive. In [A12], Göpfert *et al.* analyze the intuitiveness of various ML algorithms. Users are asked to select points in a 2-D grid used as examples for the ML algorithm. If the ML algorithm is intuitive, it is expected that users become better at selecting the training points over time, thus gaining an intuition of the algorithm's behavior.

Hybrid human–artificial intelligence (H-AI) is an evolution of human–machine interaction that integrates both human intelligence and AI into a single entity, thus forming a new enhanced intelligence. In social computing (generated by the social and interactive human behaviors using computing technology), H-AI presents a substantial advantage in tackling social-oriented problems compared with more traditional AI techniques. In [A13], Wang *et al.* present a survey of existing social computing methods (social network, swarm intelligence, social media, personality, and affective computing) and the data-related issues. The authors consider the relationship between humans and machines, defining three progressive levels (human–computer interaction, human–machine cooperation, and human–computer fusion) and proposing a layered framework for H-AI. A case study on intelligent voice assistants is presented.

D. AI in Promoting a Human-Centered AI Perspective to Improve Trust in AI

This is an interesting topic that emerged from the SI contributions and relates to the study of the users' experience with AI. The human-centered AI perspective is part of the rising trend that sees human needs as a central factor in the development of new technologies. Thanks to the study of the human experience, it is possible to understand how to facilitate AI acceptance and improve human trust in AI.

In [A14], Fietta *et al.* have given an overview of the users' general attitudes toward AI technologies. The authors highlight that several studies in the literature have shown how people display an ambiguous attitude towards AI: while users recognize the positive impact that AI technologies may have on the individual and society, they express doubts and concerns related to possible implications, such as privacy violation, replacement of humans with machines in some work environments, and the hypercontrol of technology over human activities. Human nature leads people to show a dissociation between their explicit opinion and implicit attitude. Implicit attitudes, even if they are unconscious, may influence the users' behavior and choices leading to low levels of trust in technology. The authors demonstrate that dissociation between implicit and explicit attitudes also exists towards AI. Indeed, 85% of users who explicitly declared that they had a positive opinion about AI have an implicit negative or at most neutral attitude toward AI technology. The authors conclude that new technologies based on AI suffer from innate and unconscious biases, which risk undermining the users' trust and acceptance even in the field where AI may bring significant improvements (medical field and health promotion). They recommend the need to promote greater information on AI, also giving space to the positive effects of AI on society.

The issue of trust in AI is particularly relevant for specific AI applications, especially when users feel their life could be at risk if entrusted to an artificial agent such as in the case of automated vehicles.

In [A15], Zhou *et al.* review the level of trust that pedestrians have toward automated driving. Authors claim that it is fundamental that both vehicle drivers and pedestrians develop appropriate levels of trust to make automated driving accepted as pleasant and safe. Indeed, recent studies [7], [8] have confirmed that, on average, pedestrians show inadequate degrees of trust, ranging from exceeding confidence to complete distrust. Zhou *et al.* identified three factors that influence pedestrians' trust in automated vehicles: the individual characteristics of the pedestrians, the experience with the automation, and the surrounding environments. These factors generate a conceptual model where three different types of trust are considered: dispositional, situational, and learned. The authors conclude that much work remains to be done to comprehensively understand the most effective strategies to influence pedestrians' levels of trust. Future studies should explore factors that characterize the pedestrians' trust in automated driving vehicles.

In [A16], Ayoub *et al.* investigate trust in dynamic situations as driving. The authors assume that trust is built over time and seek to understand how this process supports the acceptance and adoption of automated vehicles, specifically during control transitions between vehicles and humans. They evaluate the dynamic situational trust by combining self-reported and behavioral measures. The results showed that participants quickly adjusted their self-reported situational trust levels, which were consistent with various accuracy levels of system performance. However, participants' trust was affected by the trust preconditions. The overtrust precondition significantly increased the participants' willingness to take over control before seeing the vehicle's decision while undertrust precondition significantly decreased the participants' willingness to change their previous takeover decision after seeing the vehicle's decision.

From a human-centered view, the study of the mental models and representations formulated by humans about AI is fundamental to understanding how trustiness may be improved.

In [A17], Tenhundfeld *et al.* analyze the mental model that virtual personal assistant (VPA) users have over their devices. Indeed, most of the time, VPAs are simultaneously present on multiple devices: users might assume that the VPAs they interact with all share the same identity while other users might rely on the assumption that they have no connection. Results showed that there was no agreement on whether VPAs are part of the same interconnected system or are to be considered as single units. Furthermore, increased experience in dealing with VPAs does not influence the mental model of the subject (individuality or interconnection). The authors emphasize that various degrees of trust might explain the inconsistencies. The consumers' individual characteristics lead to differences at the level of the so-called "perfect automation scheme" (PAS) that refers to the level of human's confidence in automation technologies. The authors conclude by highlighting the crucial role of PAS.

Another field where the human-centered perspective is central relates to the design of smart environments. In [18], Reig *et al.* formulate five design lenses for smart environments that may help adapt to new technologies. The first lens concerns the features that make an environment smart. An environment may be primarily defined as "emergent" when it derives from the accumulation of different subparts. An environment is defined as "designed" when the different subparts are grouped following a top–down process. The second lens is about the alternative aims that might drive a smart environment: some environments seek to create a successful experience for the user while others have opposite objectives such as giving urgency to technological development. Third, a smart environment must be able "to adapt" itself and meet the need of constantly evolving users by providing a certain degree of versatility and openness to new technologies. Another key distinction is between those environments that are smart to increase their usability and those that are smart by their intrinsic characteristic. The last issue that should be considered is the environment's way of being triggered. The user is sometimes responsible to direct a specific request toward one of the environment's subparts. On other occasions, the environment itself may react spontaneously to an external stimulus, thanks to its internal model. In the conclusion of the review, the authors underline that the recent literature on smart environments focuses only on "smart homes" [9]–[11]. They emphasize that soon smart environments will be not limited to houses, and those studies concerning other smart contexts (offices, hospitals, research stations) will benefit from attention to the notion of human centeredness and that directing the design of the smart environments under a human-centered perspective will be crucial.

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APPENDIX
RELATED ARTICLES

[A1] D. Zhou, E. I. Barakova, P. An and M. Rauterberg, "Assistant robot enhances the perceived communication quality of people with dementia: A proof of concept," *IEEE Trans. Human-Mach. Syst.*, early access, Oct. 18, 2021, doi: 10.1109/THMS.2021.3112957.

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