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Conceptualizing the Integration of Cognitive and Physical Models to Enable Continuous Human-Robot Interaction

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***Abstract*—Research in human-robot interaction (HRI) often puts emphasis on either the cognitive level or on the physical level. In a scenario, where a robot physically guides a person to perform a complex series of tasks (e.g., a patient making tea), information is exchanged on the cognitive level and forces/torques are exchanged on the physical level, continuously. Such a continuous co-adaptive interaction between both agents and the environment requires the robot to be anticipating, proactive, and able to react flexibly to the user's intentions and situation context. The unification of sequential cognitive situation modeling and continuous robotic movement control is a challenge currently missing a conceptual framework. We conceptualize strategies on how to connect models of physical HRI and models of cognitive HRI, depending on the level of assistance provided by the robot system, from mere warnings of dangerous situations (level 1) to on-body continuous movement guidance (level 4). In this, we consider the requirements for the robot to be aware of the interaction environment and have a dynamic representation of the individual user. Our conceptual framework is intended to spark discussions and formalize assistance approaches with the aim to integrate cognitive and physical human-robot interaction approaches for anticipatory assistance in continuous dynamic tasks.**

***Index Terms*—human-robot interaction, cognitive modeling**

I. Introduction

Robots are becoming more common in the industry, healthcare, and people's households, where they directly interact with and provide assistance to humans. Existing human-robot interaction (HRI) research usually focuses either on interactions on the cognitive level (cHRI; e.g., social interactions) or on the physical level (pHRI; e.g., physical interactions with robotic assistive devices; [1]). However, regardless of the type of assistive device (robotic arm or wearable device), real-life HRI is often embodied interaction (Figure 1). This involves both information exchange on the cognitive level (e.g., [2]) and force exchanges on the physical level (e.g., [3]) at the same time. To improve the quality of HRI and develop robots that can facilitate humans better in daily life, particularly in tasks where the human receives *continuous support* [4] through a complex sequence of actions, it is important to consider how these two types of interactions align within the specific task environment, and how the alignment differ among individuals.

Different from sequential support, where the robot waits for the human to complete actions and then decides how to support them, continuous support emphasizes proactive capabilities where the robot can already anticipate and be ready to support the human in time [4]. For example, for a robotic assistive device that supports patients with motor control impairments in their daily activities such as tea making, it is crucial that the robot can anticipate risky events (e.g., spilling hot water) and warn or assist the user along with their actions seamlessly (Figure 3). We will follow this example application scenario for the rest of the paper.

In such real-life HRI, on the cognitive level, the interaction

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Fig. 1. Example of an embodied human-robot interaction: Here a robotic arm collaboratively making tea with the person. Such a task involves both cognitive interaction and force exchange on the physical level.

requires the human agent and the robotic agent to adapt to each other through inferring intentions, predicting actions, and selecting actions accordingly given the environment [5]–[8]. On the physical level, the interaction requires the human agent and the robotic agent to align their movements and interactive forces given the common goal. Therefore, we believe that HRI research needs to go beyond the current hardware (e.g., motors and sensors) and software (e.g., image processing and user motion decoding) development for robots. We postulate that it is necessary to develop unified models of cognitive and physical HRI *for the robots to have a representation of the individual user and a shared representation of the task environment with the user* [6].

This unified representation poses a theoretical challenge that requires: 1) a cognitive model that traces and anticipates the individual sequences of decisions and events, and 2) an approach that adapts to the individual specification such as variations of movements and distortions estimated by a neuromusculoskeletal model. In addition, both models need to be online-updated with multi-modal sensor data from the human user, such as eye-tracking and motion capture data to provide continuous support.

In this paper, we propose our perspective to address this theoretical challenge by presenting a theoretical framework for creating such a unified HRI model for the robotic agent. Our framework incorporates the cognitive model and the neuromusculoskeletal model of the individual human agent and anticipates the task situation as it evolves for the individual (Figure 2). We also discuss how such a unified HRI model can vary depending on levels of interactions, assistance, or individual differences within the application scenario introduced above, where a robot assists motor-impaired individuals in making tea (Figure 3).

II. Related work

A. Existing work

Researchers in HRI are already developing systems towards providing continuous support, even though different terminologies have been used. From current work that emphasizes the need for continuous support in HRI, we identify two major aspects: prediction of action plans and sequences for anticipatory HRI, and creating continuous support through providing smooth interaction methods.

Anticipatory human-machine interaction focuses on the machine's ability to predict mental states of their users in order to understand users' intentions, goals, and needs [9]. This allows the machine to anticipate user actions and provide proactive supports at the appropriate moment. Anticipation can be realized through using mental models and interaction context or situations for systems to dynamically build up expectations of intentions and goals [9].

One core aspect of the machine's ability to anticipate is to perceive, understand, and predict the user's intentions and actions. This can be achieved through both rule-based and data-driven approaches [10]. Rule-based approaches focus on semantic reasoning. For example, Enriched Semantic Event Chain framework has been applied to represent dynamic spatial relationships between objects and the manipulating agent [11], [12]. Data-driven approaches often require a large amount of training data for action recognition and prediction for the robot to perceive and reason about the environment.

However, both approaches in real-life HRI often require the robotic system to interpret and incorporate multi-modal data of the user and the interaction scenario. For example, robotic systems can monitor the user's gaze for intent prediction, and proactively collaborate with the user according to its predictions [13]–[17]. Some robotic systems have also been developed to learn about the interactive situation directly through affordance-based reasoning (e.g., [18]). In such systems, the robot can predict and anticipate actions based on its recognized object and situation affordances.

To provide continuous support, the robotic system also needs to plan and generate adaptive actions [19]–[21]. Currently, this is often achieved via joint planning for collaboration and interaction primitives [22]. In addition, large language models (LLMs) have also been implemented in the HRI framework [23] for semantic planning and generating low-level actions. We provide more background on models for cognitive and physical HRI in the next section.

B. Models of cognitive and physical human-robot interactions

Research in recent years has already implemented the idea of combining cognitive and physical planning for robot task planning in human-robot collaborations. This includes avoiding interfering human movements in the task space through planning with learned human motion trajectories [24], using human-aware control-based methods for a collaborative task where the human and the robot complete a mosaic together [25], etc. In addition, there is also work focusing on the robot's cognitive task planning for robot learning [26] and moving trajectory planning for the robot to deal with uncertainty in the HRI environment [27]. However, to provide humans with task assistance that requires the robot to *anticipate* the human and involves *force exchanges* (either directly or through an object that the human and the robot carry jointly), a great challenge still remains: the robot not only needs to detect and monitor individual user's long-term (e.g., making tea) and short-term intentions (e.g., picking up a mug) and the user's capabilities in order to determine the required assistance in the *joint* task, but also need to do so in real time.

Recent work in cognitive science and HRI provides the background to develop unified models of HRI for robotics that have a representation of the human, provides a possibility to interface models of cHRI and pHRI for personalized HRI [6], and maintains awareness of the task situation.

On the cognitive level, the robotic agent needs to understand the intentions of the human agent and align its strategy with that of the human agent. This process could be achieved with forward (generative) models and/or inverse models [5]. Modeling approaches include connectionist models such as neural networks [28], Bayesian models [29], and cognitive architectures (e.g., ACT-R, [30]–[34], SOAR, [35], EPIC, [36], EPAM, [37]). Forward (generative) models of human planning and decision making can help to make predictions of human choices and behaviors given the human agent's task goal and the current state as inputs. These models can be informed by the framework of computational rationality [38], [39] and benefit from rational analysis [5], where the human agent's individual cognitive bounds and environmental bounds are considered in models of human decisions.

Besides forward models, inverse models can also be useful when the robotic agent needs to approach the goal of value alignment [40], [41] through inferring the human's intentions, goals, or beliefs given observations of human behaviors and decisions as inputs (e.g., through theory of mind; [42]–[44]). These models could be particularly helpful when the ability to anticipate [45] is needed by the robotic agent in more complex tasks where the robotic agent needs to predict future states of the human agent and the environment. Anticipation may seem to be more relevant to cognitive interactions than to physical interactions [46], but for anticipation, information is needed from the physical level as well (e.g., action prediction based on eye-gaze, [46], goal inference based on behaviors, [47], communications through forces in human-robot collaborations [48]–[50]).

Cognitive interactions are connected to physical interactions through action selections and sensory feedback about the agent's own state and the changes in the environment. In these physical interactions, the robotic agent needs to determine the appropriate assistive force in order to align actions with each human agent. Therefore, on the physical level, the robotic agent is potentially required to have a representation of the human agent's sensory-motor control loop that can be adapted to individual users.

The dynamics of the human motor system can be predicted by models of the "sensorimotor loop" [51]. Sensorimotor forward models estimate state and context given the motor command and the previous state as input [51], [52]. Inverse models contribute to motor planning [53], [54] and the generation of desired trajectories given the state, context, and task as inputs [55]. Such representations potentially link higher-level cognition to more detailed motor programs and explain the generation of motor commands [51]. These models therefore provide an important theoretical foundation for interfacing models of cognitive and physical HRI.

One possibility of unifying cognitive states and physical interactions is through the predictive processing framework [56] (e.g., Free Energy Principle [57]). For example, Kahl et al. [58] present a computational model of an autonomous agent with an active self-image with ideas based on the Free Energy Principle [57]. Their model addresses the challenge of unifying higher-level cognition and lower-level sensorimotor control while providing the autonomous agent with situational awareness [58]. Although [58] focus on modeling a single autonomous agent and their model does not include detailed motor command program, we believe that their conceptual framework can inform our goal of creating unified models of cHRI and pHRI.

Our theoretical framework implements a cognitive architecture on the cognitive level, providing a higher level of transparency for explainable connections between the cognitive level's predictions and the physical's commands during the interaction. In addition, its structured representations provide us the benefit to make use of concepts in a flexible manner. We will illustrate this further in the next section.

III. Theoretical Framework

We propose a theoretical framework to bring together pHRI and cHRI (Figure 2). In this framework, both the human agent and the robotic agent are modeled with a cognitive layer and a sensorimotor control layer, or a physical layer. The robotic agent's cognitive and physical layers correspond to those of the human agent. The robotic agent's cognitive layer is implemented as a cognitive architecture, which can be interfaced with models of the human agent's sensorimotor system (such as a neuromuscularskeletal model) on the physical layer. This framework concerns the control architecture of the robotic agent, which is to be distinguished from the hardware.

We further postulate that the robotic agent needs a model representation of the human's cognitive and sensorimotor layer to adequately select and execute collaborative or assistive actions.

Our envisioned application of such a framework is to develop unified models of HRI to provide better interaction with and assistance to the human agent. During the interaction, on the cognitive layer, having a full representation of the human agent's cognitive processes and directly simulating human behaviors in the task could be extremely computationally expensive. Therefore, in practice, we propose that it could be sufficient for the robotic agent to understand the task goals and anticipate the human agent's actions and the situation or the interaction environment in order to provide assistance adapted to individual users in potentially risky or dangerous situations.

To achieve such anticipation and situation awareness, as stated above, it is important for the robot to have a representation of the individual user, and for the robotic agent and the human to have a shared representation of the task [6]. Usually

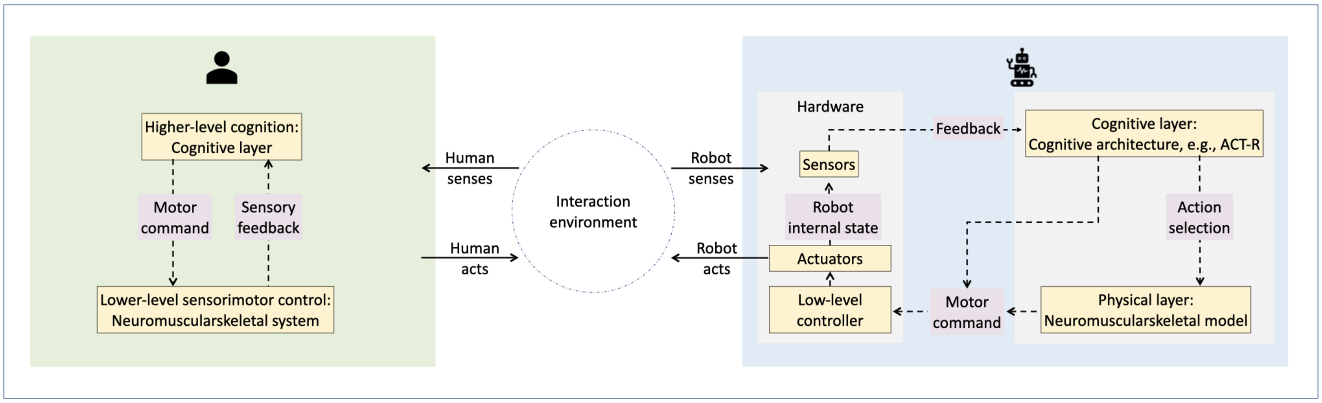

Fig. 2. A theoretical framework to connect models of pHRI and cHRI. In this framework, both of the human agent and the robotic agent have a cognitive layer and a physical layer (to be distinguished from the hardware). The robotic agent's cognitive layer is implemented as a cognitive architecture, which can be interfaced with models of the human agent's sensorimotor system on the physical layer.

cognitive models of individuals show cognitive processes in a well controlled experiment. In an anticipatory cognitive model representing the individual user for the robot, we focus on receiving information from the particular human subject, such as eye-gaze to some AOI or some specific action. The model interprets what this means regarding a shared task representation, situation understanding, the user's cognitive state, and the user's next possible action or decision. This anticipatory model type is some kind of more abstract model of the individual in a dynamic situation in which several decisions are made which have an influence on the situation and the environment (similar to model tracing, see [59] for an example).

In addition, knowledge of the human agent's skills is also important, as different individuals may have different repertoire of movements. With such information, the robotic agent can keep track of task information, goals, and select actions adapted to the human agent. Potentially, through this process of action selection and robot state feedback, the robotic agent's cognitive layer can be interfaced with its physical layer. For example, as the robot's cognitive layer makes a decision on what action to take (e.g., reach a specific location), a "motor command" is given to the robot's physical layer. In turn, the robot's state and what it senses from the interaction environment are given to its cognitive layer as a "sensory feedback".

The robot's physical layer can include representations of the human agent's sensorimotor system (e.g., [52]), particularly when detailed models of the human's movement trajectories and interactive forces are necessary for the robot to estimate the precise support needed. The robotic agent may also benefit from learning representations based on interaction primitives on the physical layer, which can potentially improve the robot's flexibility and adaptivity for its physical interactions with the human [22].

In the following sections, we propose one method to interface the robot's cognitive layer with its physical layer—by implementing the robot's cognitive layer as an ACT-R model. We then use our application example where a human agent and an assistive robotic agent interact in a tea-making task to further illustrate different levels of assistance by the robotic agent.

A. Requirements for interfacing cognitive layer and physical layer

To interface the robot's cognitive layer and physical layer, we need to consider how information about both agents' states and information from the interaction environment can be taken into account, and how the cognitive layer's model output can serve as the physical layer's model input. For example, the cognitive level may determine that the goal of the human is to lift and move an object from an initial position to a desired position and that support is needed for this action. It gives the initial position and desired final position to the physical layer model.

The robot's physical layer contains a model representation of the human's sensorimotor control system. Upon receiving the humans starting position and estimated final position the sensorimotor model predicts the human's movement trajectory and desired assistive force [52], [55], [60], [61]. It may also consider electrophysiological data (e.g., data from EEG or EMG [62]). With target position, desired final pose for the robot, and desired assistive force, inverse kinematics and dynamics can be applied to develop a motor plan for the robotic agent [63].

We propose that one possible implementation of the robotic agent's cognitive layer can be an ACT-R cognitive architecture [30], a prominent type of cognitive architecture that provides a theory of the structure of the human mind with a certain level of abstraction [64]. First, ACT-R's modular structure allows us to provide the robotic agent's cognitive layer with a representation of the task knowledge, the ability to process information about both agents' states and the environment for situation awareness, and potentially even the ability to learn [34]. Second, its structure provides a possibility to interface the robotic agent's cognitive layer with models of the human's neuromusculoskeletal system or interaction primitives [22] on the robotic agent's physical layer.

For exmaple, the ACT-R model predicts the next most likely action based on its internal state and multimodal sensor input, e.g., eye-gaze information. The neuromusculoskeletal model then receives the current state of the arm (from kinematic sensors) and the next most likely action (e.g., putting the tea bag into the cup). From this information, the neuromusculoskeletal model predicts the natural movement and proprioceptive feedback about the movement and about contact with objects in the environment. If deviations from this predicted movement are recognized, they will be classified as ”impaired movements” or ”alternative actions”, as an input for the ACT-R model.

Multimodal data can be processed in real time based on robotic software architectures, such as Robot Operating System ROS2. Sensor Fusion is possible based on Kalman-Filter approaches. Recent developments in biomechanical simulation engines have massively reduced the compute time such that real-time predictions become possible [65], [66]

In our example where a human is making tea with the help of a robotic assistive device, we assume that the task-specific knowledge such as the task goal (making tea), task constraints (injury prevention), object locations, and the potential steps involved is given to the cognitive model of the robotic agent, possibly as *chunks* in the *declarative memory module*. The robotic agent does not necessarily know the exact details of how to make tea, but rather the crucial sub-tasks such as ”boiling water” and ”put hot water in the mug”. As the human agent performs sequences of actions (e.g., pour water in the kettle), the task situation changes. By processing information about the interaction environment (e.g., via the *visual module* of the architecture) such as whether the water in the kettle is hot, the robotic agent becomes aware of the state of the task situation possibly by modifying the values of *chunks* in the *imaginal buffer* of the architecture (e.g., the value for whether the water is hot is changed to ”yes”). Then, the robotic agent can make predictions about the human agent's following action. If there is potential danger such as when the water has been boiled and there are tea leaves in the mug, the robotic agent may predict that the human agent is likely to pour hot water into the mug next and that there is a possibility of spilling hot water. If appropriate, the cognitive model can select and initiate an action to support the human agent. If this requires physical human-robot interaction, the support will be determined by considering the sensorimotor model of the human and her/his impairment.

B. Levels of assistance in a tea-making application scenario

Robotic assistive devices are envisioned to provide help and support patients with motor control impairments, such as a tremor—possibly due to some neurodegenerative disease [67]—in their everyday life [68]–[72]. Such an assistive device can either be a robotic arm or a wearable assistive device.

When patients experiencing a tremor episode while making tea, they may accidentally spill hot water and burn themselves. To prevent such potential injuries, the robotic agent needs to have an understanding of the task and the human agent, as well as to anticipate the risky situations.

We categorize the possible assistance that the robotic agent could provide into four levels. The interaction between the human agent and the robotic agent becomes more interleaved and therefore potentially more complicated to realize in each level. We illustrate the requirements for the robotic agent on the cognitive layer and on the physical layer in each level in a tea-making process as shown in Figure 3.

The first level of assistance is to provide the patient with an alert when there is a potential for danger. While making tea, the robotic agent needs to be aware when there is hot water involved (task state) and if the patient shows tremor symptoms (sensory motor state) to generate appropriate warnings. This level may not require physical interactions between the human agent and the robotic agent. For the second level of assistance, the robotic agent can take over the entire action completely when the scenario is dangerous—such as pouring hot water into the tea mug or carrying the mug with hot tea. This level of assistance does not necessarily involve physical interactions either, yet it involves the robotic agent to send ”motor commands” from its cognitive layer to its physical layer. For the third level of assistance, the robotic agent provides guidance to the human agent, when necessary—for example, the robotic agent may guide the human agent to move their arm on a specific trajectory stably when pouring water. And for the fourth level of assistance, the robotic agent provides only the force or support needed during the movements, collaborating with the human agent. While both of the third and the fourth levels contain physical interactions between the human agent and the robotic agent, the latter requires more detailed understanding of the human agent's motor system in order for the robotic agent to estimate the amount of support to provide without compromising the human agent's sense of control (agency).

IV. Limitations

We also acknowledge several limitations in our framework. First, our framework provides possibilities of connecting models of cognitive and physical interactions on a fairly high and abstract level. Therefore, practical details and feasibility of implementation still need to investigated further in specific use cases. Second, developing models for HRI in real-world scenarios, including our application example, still face the challenges of accurately interpreting user's intentions in unpredictable environments and intricate tasks. This requires continuous advancements of computational models that can predict and anticipate human intentions *across different contexts* in real life, and the alignment between those predictions with models of physical HRI in real time.

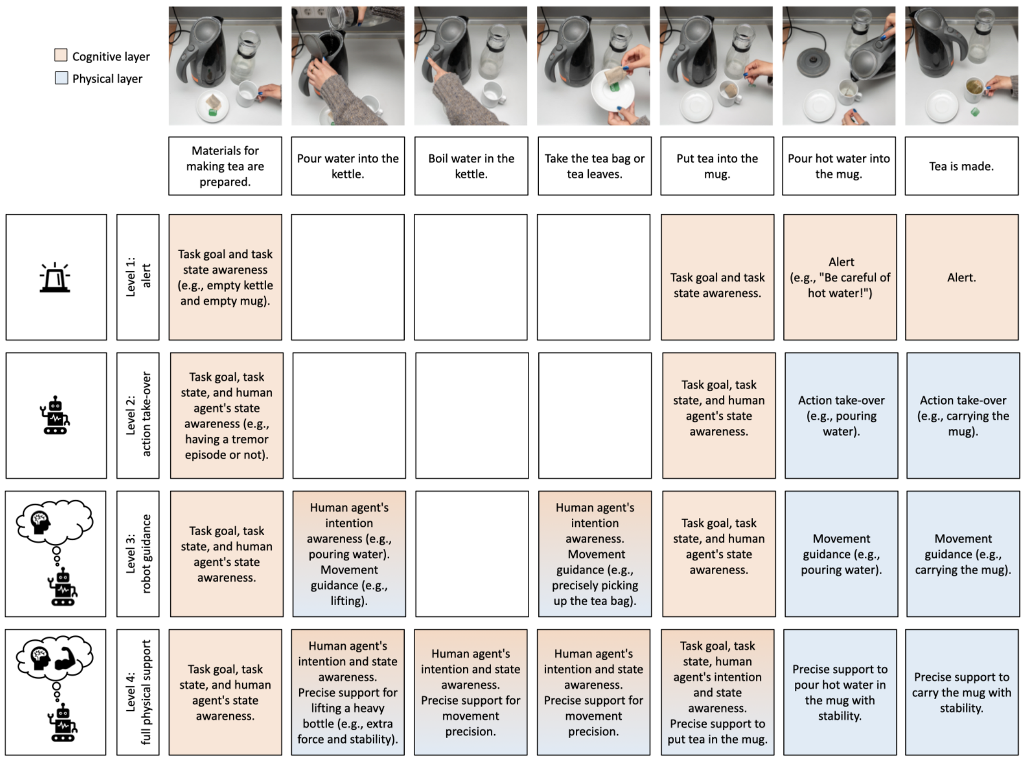

Fig. 3. An example of the process of making tea, and four levels of assistance that the robotic agent can potentially provide, color-coded by the requirement from the cognitive and the physical layers of the robotic agent (orange: cognitive layer; blue: physical layer; orange and blue: both layers).

V. Conclusion

We present a conceptual framework that attempts to integrate models of cognitive and physical HRI through interfacing a cognitive architecture with a model representing the human user's sensorimotor system. According to Wilson's six views of embodiment [73], embodied cognition is situated at the center of what we want to achieve with this framework. We also discuss how this framework could potentially be applied to an anticipatory, situation-aware robotic agent providing the human agent with support that can adapt to different individuals.

Our approach addresses the adaptation to individual differences on several aspects. First, with such a unified architecture, we go beyond anticipating the individual human agent's goals and intentions with a cognitive model, and try to also anticipate their physical behaviors with a neuromusculoskeletal model, e.g., how movements can change depending on the severeness of tremor—which will change over time. Second, depending on how the individual traces of actions and the interaction dynamics change, our model provides the possibility to predict step-by-step short-term intentions flexibly given the prediction of individual long-term intentions. Last but not least, by emphasizing the shared representation of the task between the robot and the human, our proposed framework has the potential to adapt to different individual situation representations.

We claim that the integration of such considerations and the support of input data from the human agent during the interaction (e.g., eye-gaze data, motion-tracking data, etc.) are mandatory for equipping the robot with a good anticipatory model of the individual. We believe that our concept of a unified framework provides a theoretical foundation and will enable novel directions for future human-centered HRI research and applications.

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References

[1] C. Bartneck, T. Belpaeme, F. Eyssel, T. Kanda, M. Keijsers, and S. Šabanović, *Human-robot interaction: An introduction*. Cambridge University Press, 2020.

[2] B. Mutlu, N. Roy, and S. Šabanović, "Cognitive human–robot interaction," *Springer handbook of robotics*, pp. 1907–1934, 2016.

[3] S. Haddadin and E. Croft, "Physical human–robot interaction," in *Springer handbook of robotics*. Springer, 2016, pp. 1835–1874.

[4] P. Wintersberger, N. Van Berkel, N. Fereydooni, B. Tag, E. L. Glassman, D. Buschek, A. Blandford, and F. Michahelles, "Designing for continuous interaction with artificial intelligence systems," in *CHI Conference on Human Factors in Computing Systems Extended Abstracts*, 2022, pp. 1–4.

[5] M. K. Ho and T. L. Griffiths, "Cognitive science as a source of forward and inverse models of human decisions for robotics and control," *arXiv:2109.00127 [cs, eess]*, Aug. 2021, arXiv: 2109.00127.

[6] T. Schürmann and P. Beckerle, "Personalizing Human-Agent Interaction Through Cognitive Models," *Frontiers in Psychology*, vol. 11, p. 561510, Sep. 2020.

[7] P. Beckerle, C. Castellini, and B. Lenggenhager, “Robotic interfaces for cognitive psychology and embodiment research: a research roadmap,” *Wiley Interdisciplinary Reviews: Cognitive Science*, vol. 10, no. 2, p. e1486, 2018.

[8] P. Beckerle, G. Salvietti, R. Unal, D. Prattichizzo, S. Rossi, C. Castellini, S. Hirche, S. Endo, H. B. Amor, M. Ciocarlie *et al.*, “A human–robot interaction perspective on assistive and rehabilitation robotics,” *Frontiers in neurorobotics*, vol. 11, p. 24, 2017.

[9] J. Borst, A. Bulling, C. Gonzalez, and N. Russwinkel, “Anticipatory human-machine interaction (dagstuhl seminar 22202),” 2022.

[10] J. Borst, A. Bulling, E. Dietz, C. Hao, F. Keller, F. Strohm, A. I. Sburlea, S. Kaski, E. André, and H. Admoni, “4.3 data-driven vs. rule-based models for anticipation,” *Anticipatory Human-Machine Interaction*, p. 157.

[11] F. Ziaeetabar, T. Kulvicius, M. Tamosiunaite, and F. Wörgötter, “Prediction of manipulation action classes using semantic spatial reasoning,” in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2018, pp. 3350–3357.

[12] F. Ziaeetabar, S. Pfeiffer, M. Tamosiunaite, T. Kulvicius, and F. Wörgötter, “Who can predict faster? human or robot?”

[13] C.-M. Huang, S. Andrist, A. Sauppé, and B. Mutlu, “Using gaze patterns to predict task intent in collaboration,” *Frontiers in psychology*, vol. 6, p. 1049, 2015.

[14] K. Ruhland, C. E. Peters, S. Andrist, J. B. Badler, N. I. Badler, M. Gleicher, B. Mutlu, and R. McDonnell, “A review of eye gaze in virtual agents, social robotics and hci: Behaviour generation, user interaction and perception,” in *Computer graphics forum*, vol. 34, no. 6. Wiley Online Library, 2015, pp. 299–326.

[15] C.-M. Huang and B. Mutlu, “Anticipatory robot control for efficient human-robot collaboration,” in *2016 11th ACM/IEEE international conference on human-robot interaction (HRI)*. IEEE, 2016, pp. 83–90.

[16] Y. Terzioğlu, B. Mutlu, and E. Şahin, “Designing social cues for collaborative robots: the role of gaze and breathing in human-robot collaboration,” in *Proceedings of the 2020 ACM/IEEE international conference on human-robot interaction*, 2020, pp. 343–357.

[17] H. Su, W. Qi, J. Chen, C. Yang, J. Sandoval, and M. A. Laribi, “Recent advancements in multimodal human–robot interaction,” *Frontiers in Neurorobotics*, vol. 17, p. 1084000, 2023.

[18] M. Imre, E. Oztop, Y. Nagai, and E. Ugur, “Affordance-based altruistic robotic architecture for human–robot collaboration,” *Adaptive Behavior*, vol. 27, no. 4, pp. 223–241, 2019.

[19] A. Agostini, C. Torras, and F. Wörgötter, “Efficient interactive decision-making framework for robotic applications,” *Artificial Intelligence*, vol. 247, pp. 187–212, 2017.

[20] W. Kim, J. Lee, L. Peternel, N. Tsagarakis, and A. Ajoudani, “Anticipatory robot assistance for the prevention of human static joint overloading in human–robot collaboration,” *IEEE robotics and automation letters*, vol. 3, no. 1, pp. 68–75, 2017.

[21] C.-M. Huang, M. Cakmak, and B. Mutlu, “Adaptive coordination strategies for human-robot handovers.” in *Robotics: science and systems*, vol. 11. Rome, Italy, 2015, pp. 1–10.

[22] H. B. Amor, G. Neumann, S. Kamthe, O. Kroemer, and J. Peters, “Interaction primitives for human-robot cooperation tasks,” in *2014 IEEE international conference on robotics and automation (ICRA)*. IEEE, 2014, pp. 2831–2837.

[23] M. Rohrmüller, Y. Ren, P.-R. Schlumbom, A. Bifet, P. Beckerle, and A. Dwivedi, “Perspectives on using multi-modal large language models for physical human-robot interaction,” in *40th Anniversary of the IEEE International Conference on Robotics and Automation*. IEEE, 2024.

[24] J. Mainprice and D. Berenson, “Human-robot collaborative manipulation planning using early prediction of human motion,” in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2013, pp. 299–306.

[25] S. Sandrini, M. Faroni, and N. Pedrocchi, “Learning action duration and synergy in task planning for human-robot collaboration,” in *2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA)*. IEEE, 2022, pp. 1–6.

[26] D. Paulius, A. Agostini, and D. Lee, “Long-horizon planning and execution with functional object-oriented networks,” *IEEE Robotics and Automation Letters*, vol. 8, no. 8, pp. 4513–4520, 2023.

[27] M. Saida, J. R. Medina, and S. Hirche, “Adaptive attitude design with risk-sensitive optimal feedback control in physical human-robot interaction,” in *2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication*. IEEE, 2012, pp. 955–961.

[28] M. S. Thomas and J. L. McClelland, “Connectionist models of cognition.” 2008.

[29] T. Schürmann, J. Vogt, O. Christ, and P. Beckerle, “The Bayesian causal inference model benefits from an informed prior to predict proprioceptive drift in the rubber foot illusion,” *Cognitive Processing*, vol. 20, no. 4, pp. 447–457, Nov. 2019. [Online]. Available: http://link.springer.com/10.1007/s10339-019-00928-9

[30] J. R. Anderson, *How can the human mind occur in the physical universe?* Oxford University Press, 2009.

[31] S. Prezenski, A. Brechmann, S. Wolff, and N. Russwinkel, “A Cognitive Modeling Approach to Strategy Formation in Dynamic Decision Making,” *Frontiers in Psychology*, vol. 8, p. 1335, Aug. 2017. [Online]. Available: http://journal.frontiersin.org/article/10.3389/fpsyg.2017.01335/full

[32] S. Prezenski, “Implementing Mental Model Updating in ACT-R,” *Proceedings of the 15th International Conference on Cognitive Modeling*, p. 7, 2017.

[33] G. Trafton, L. Hiatt, A. Harrison, F. Tanborello, S. Khemlani, and A. Schultz, “ACT-R/E: An Embodied Cognitive Architecture for Human-Robot Interaction,” *Journal of Human-Robot Interaction*, vol. 2, no. 1, pp. 30–55, Mar. 2013. [Online]. Available: http://dl.acm.org/citation.cfm?id=3109702

[34] U. Kurup and C. Lebiere, “What can cognitive architectures do for robotics?” *Biologically Inspired Cognitive Architectures*, vol. 2, pp. 88–99, 2012.

[35] A. Newell, *Unified theories of cognition*. Harvard University Press, 1994.

[36] D. E. Meyer and D. E. Kieras, “A computational theory of executive cognitive processes and multiple-task performance: Part i. basic mechanisms.” *Psychological review*, vol. 104, no. 1, p. 3, 1997.

[37] E. A. Feigenbaum and H. A. Simon, “Epam-like models of recognition and learning,” *Cognitive Science*, vol. 8, no. 4, pp. 305–336, 1984.

[38] S. J. Gershman, E. J. Horvitz, and J. B. Tenenbaum, “Computational rationality: A converging paradigm for intelligence in brains, minds, and machines,” *Science*, vol. 349, no. 6245, pp. 273–278, 2015.

[39] R. L. Lewis, A. Howes, and S. Singh, “Computational rationality: Linking mechanism and behavior through bounded utility maximization,” *Topics in cognitive science*, vol. 6, no. 2, pp. 279–311, 2014.

[40] J. F. Fisac, M. A. Gates, J. B. Hamrick, C. Liu, D. Hadfield-Menell, M. Palaniappan, D. Malik, S. S. Sastry, T. L. Griffiths, and A. D. Dragan, “Pragmatic-pedagogic value alignment,” in *Robotics Research*. Springer, 2020, pp. 49–57.

[41] D. Malik, M. Palaniappan, J. Fisac, D. Hadfield-Menell, S. Russell, and A. Dragan, “An efficient, generalized bellman update for cooperative inverse reinforcement learning,” in *International Conference on Machine Learning*. PMLR, 2018, pp. 3394–3402.

[42] M. Berke and J. Jara-Ettinger, “Thinking about thinking through inverse reasoning,” 2021.

[43] J. Jara-Ettinger, “Theory of mind as inverse reinforcement learning,” *Current Opinion in Behavioral Sciences*, vol. 29, 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2352154618302055

[44] N. Rabinowitz, F. Perbet, F. Song, C. Zhang, S. A. Eslami, and M. Botvinick, “Machine theory of mind,” in *International conference on machine learning*. PMLR, 2018, pp. 4218–4227.

[45] G. Klein, D. Snowden, and C. L. Pin, “Anticipatory thinking,” in *Informed by Knowledge*. Psychology Press, 2011, pp. 249–260.

[46] R. M. Aronson, N. Almutlak, and H. Admoni, “Inferring goals with gaze during teleoperated manipulation,” in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2021, pp. 7307–7314.

[47] A. Taylor, E. Mamantov, and H. Admoni, “Wait wait, nonverbally tell me: Legibility for use in restaurant navigation,” in *Proceedings of RSS '21 2nd Workshop on Social Robot Navigation*, July 2021.

[48] A. Ajoudani, A. M. Zanchettin, S. Ivaldi, A. Albu-Schäffer, K. Kosuge, and O. Khatib, “Progress and prospects of the human–robot collaboration,” *Autonomous Robots*, vol. 42, no. 5, pp. 957–975, 2018.

[49] F. Ficuciello, L. Villani, and B. Siciliano, “Variable impedance control of redundant manipulators for intuitive human–robot physical interaction,” *IEEE Transactions on Robotics*, vol. 31, no. 4, pp. 850–863, 2015.

[50] R. Ikeura and H. Inooka, “Variable impedance control of a robot for cooperation with a human,” in *Proceedings of 1995 IEEE International*

Conference on Robotics and Automation, vol. 3. IEEE, 1995, pp. 3097–3102.

[51] D. M. Wolpert and Z. Ghahramani, "Computational principles of movement neuroscience," *Nature neuroscience*, vol. 3, no. 11, pp. 1212–1217, 2000.

[52] K. Stollenmaier, I. S. Rist, F. Izzi, and D. F. Haeufle, "Simulating the response of a neuro-musculoskeletal model to assistive forces: implications for the design of wearables compensating for motor control deficits," in *2020 8th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)*. New York City, NY, USA: IEEE, Nov. 2020, pp. 779–784.

[53] H. R. Sheahan, D. W. Franklin, and D. M. Wolpert, "Motor planning, not execution, separates motor memories," *Neuron*, vol. 92, no. 4, pp. 773–779, 2016.

[54] K. P. Körding and D. M. Wolpert, "Bayesian integration in sensorimotor learning," *Nature*, vol. 427, no. 6971, pp. 244–247, 2004.

[55] M. Kawato, "Internal models for motor control and trajectory planning," *Current opinion in neurobiology*, vol. 9, no. 6, pp. 718–727, 1999.

[56] A. Ciria, G. Schillaci, G. Pezzulo, V. V. Hafner, and B. Lara, "Predictive processing in cognitive robotics: a review," *Neural Computation*, vol. 33, no. 5, pp. 1402–1432, 2021.

[57] K. Friston and S. Kiebel, "Predictive coding under the free-energy principle," *Philosophical transactions of the Royal Society B: Biological sciences*, vol. 364, no. 1521, pp. 1211–1221, 2009.

[58] S. Kahl, S. Wiese, N. Russwinkel, and S. Kopp, "Towards autonomous artificial agents with an active self: modeling sense of control in situated action," *Cognitive Systems Research*, vol. 72, pp. 50–62, 2022.

[59] O. W. Klaproth, M. Halbrügge, L. R. Krol, C. Vernaleken, T. O. Zander, and N. Russwinkel, "A Neuroadaptive Cognitive Model for Dealing With Uncertainty in Tracing Pilots' Cognitive State," *Topics in Cognitive Science*, vol. 12, no. 3, pp. 1012–1029, Jul. 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1111/tops.12515

[60] C. M. Harris and D. M. Wolpert, "Signal-dependent noise determines motor planning," *Nature*, vol. 394, no. 6695, pp. 780–784, 1998.

[61] T. Flash and N. Hogan, "The coordination of arm movements: an experimentally confirmed mathematical model," *Journal of neuroscience*, vol. 5, no. 7, pp. 1688–1703, 1985.

[62] W.-k. Tam, T. Wu, Q. Zhao, E. Keefer, and Z. Yang, "Human motor decoding from neural signals: a review," *BMC Biomedical Engineering*, vol. 1, no. 1, pp. 1–22, 2019.

[63] R. P. Paul, *Robot manipulators: mathematics, programming, and control: the computer control of robot manipulators*. Richard Paul, 1981.

[64] D. Marr, *Vision*. New York: Freeman, 1982.

[65] V. Caggiano, H. Wang, G. Durandau, M. Sartori, and V. Kumar, "Myosuite – a contact-rich simulation suite for musculoskeletal motor control," https://github.com/MyoHub/myosuite, 2022. [Online]. Available: https://sites.google.com/view/myosuite

[66] T. Geijtenbeek, "The Hyfydy simulation software," 11 2021, https://hyfydy.com. [Online]. Available: https://hyfydy.com

[67] A. Lenka and J. Jankovic, "Tremor syndromes: an updated review," *Frontiers in Neurology*, vol. 12, 2021.

[68] V. Castrillo-Fraile, E. C. Peña, J. M. T. G. y Galán, P. D. Delgado-López, C. Collazo, and E. Cubo, "Tremor control devices for essential tremor: A systematic literature review," *Tremor and Other Hyperkinetic Movements*, vol. 9, no. 0, dec 2019.

[69] N. P. Fromme, M. Camenzind, R. Riener, and . Rossi, René Michel, "Need for mechanically and ergonomically enhanced tremor-suppression orthoses for the upper limb: a systematic review," *Journal of NeuroEngineering and Rehabilitation*, vol. 16, no. 1, p. 93, 2019.

[70] M. Mohammadi, A. Zolfagharian, M. Bodaghi, Y. Xiang, and A. Z. Kouzani, "4d printing of soft orthoses for tremor suppression," *Bio-Design and Manufacturing*, vol. 5, no. 4, pp. 786–807, Jun. 2022.

[71] Y. Zhou, P. Daemi, B. Edmonds, Z. Habibollahi, M. E. Jenkins, M. D. Naish, and A. L. Trejos, *Mechatronic Devices for Upper Limb Tremor*. Springer International Publishing, 2023, pp. 489–526.

[72] A. Shagan Shomron, C. Chase-Markopoulou, J. R. Walter, J. Sellhorn-Timm, Y. Shao, T. Nadler, A. Benson, I. Wochner, E. H. Rumley, I. Wurster, P. Klocke, D. Weiss, S. Schmitt, C. Keplinger, and D. F. Haeufle, "A robotic and virtual testing platform highlighting the promise of soft wearable actuators for wrist tremor suppression," *Device*, p. 100719, Mar. 2025.

[73] M. Wilson, "Six views of embodied cognition," *Psychonomic bulletin & review*, vol. 9, pp. 625–636, 2002.