Interacting with Adaptive AI in Assistive Human–Robot Interaction

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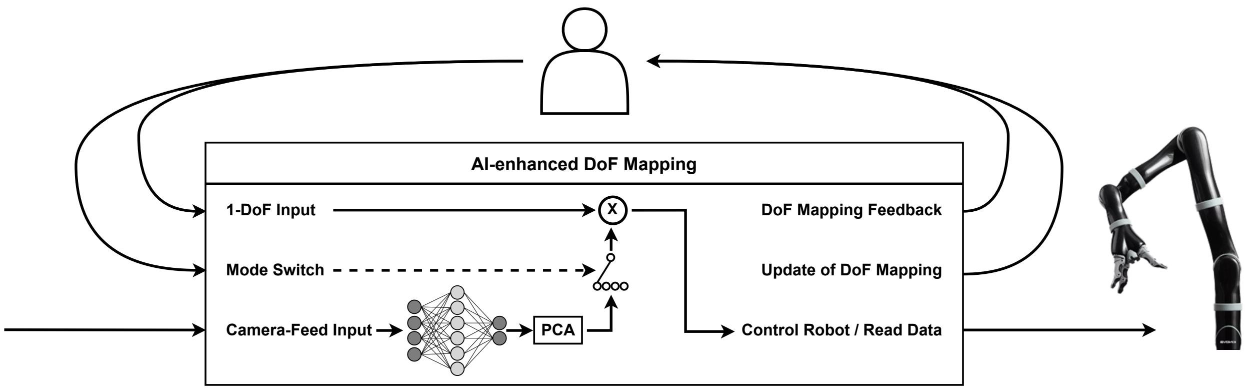

Figure 1: Overview of an AI-enhanced DoF mapping concept, which uses the camera feed to provide a shared control approach for controlling an assistive robotic arm via the control pipeline [20].

Abstract

Adaptive AI systems are increasingly embedded in everyday environments and support users beyond isolated task execution. In assistive Human-Robot Interaction (HRI), such systems operate in long-term, context-dependent, and safety-relevant settings. These characteristics impose constraints on adaptivity, autonomy, and transparency that are insufficiently addressed in much current research on interactive AI. This position paper argues that assistive HRI provides a suitable domain for examining fundamental challenges of human-AI interaction. Based on prior work in assistive and context-aware interaction, the paper identifies core interactional tensions and derives design implications for future research.

CCS Concepts

• **Computing methodologies** → *Control methods*; • **Human-centered computing** → **Interactive systems and tools**; • **Computer systems organization** → *Robotics.*

Keywords

assistive technologies, adaptive interaction, human–ai collaboration

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1 Introduction

Recent advances in artificial intelligence have enabled systems that actively participate in interaction rather than merely executing predefined functions [12, 16, 25]. Research on interactive and adaptive AI has primarily focused on conversational agents, recommender systems, and productivity-oriented applications [9]. These systems are commonly evaluated in short-term, task-bounded, or laboratory-based settings [2, 15].

Assistive Human-Robot Interaction differs substantially from these scenarios [19]. Assistive systems are integrated into users' everyday activities and support individuals in physical, cognitive, or situationally constrained contexts [14, 23, 24]. Interaction is not episodic but unfolds continuously over extended periods of time [5]. System behavior must therefore remain interpretable, predictable, and aligned with users' abilities and expectations [4, 6].

This paper positions assistive HRI as a relevant domain for research on adaptive and interactive AI systems. The central claim is that assistive contexts make interactional challenges visible that are fundamental to adaptive AI, yet remain underrepresented in much existing work.

2 Characteristics of Assistive Interaction

Assistive interaction is shaped by a combination of contextual, temporal, and ethical constraints that distinguish it from many commonly studied human-AI interaction scenarios.

2.1 Situated and Context-Dependent Operation

Assistive systems operate in dynamic physical and social environments. They must continuously interpret environmental conditions, user state, and task context. Explicit user input is often limited due to physical or cognitive constraints, requiring systems to rely on implicit signals such as movement, posture, or environmental cues [3, 10, 28]. As a result, interaction is inherently uncertain and context-sensitive.

2.2 Longitudinal Use and Evolving Expectations

Assistive interaction is longitudinal. Users interact with the system repeatedly over weeks, months, or longer. Over time, users develop routines, expectations, and mental models of system behavior [10]. Changes in system behavior, even if intended to improve performance, can disrupt these models and negatively affect acceptance [6]. Designing for stability over time therefore becomes as important as supporting adaptation.

2.3 Safety and Responsibility

Assistive systems frequently operate in safety-relevant contexts. Inappropriate actions, delayed responses, or misinterpretations of user intent can have direct consequences for user well-being [29]. This places strong constraints on system autonomy and requires careful consideration of responsibility, accountability, and user trust [4].

Together, these characteristics create interactional conditions that amplify core challenges of adaptive AI systems.

3 Interactional Tensions in Assistive AI Systems

In the following, interactional stability refers to the preservation of consistent and predictable system behavior over time, enabling users to form and maintain reliable mental models despite adaptive system changes. Assistive AI systems are shaped by recurring tensions that arise from the need to balance system adaptivity with interactional stability and user-centered requirements.

3.1 Adaptivity and Predictability

Adaptation enables systems to respond to changing contexts and user needs. However, adaptive behavior can reduce predictability, making it difficult for users to form stable mental models [11]. In assistive contexts, predictability often outweighs optimal performance, as users rely on consistent behavior to maintain control and confidence [17].

This tension highlights the need to distinguish between functional adaptation and interactional stability. Improvements in system intelligence do not necessarily translate into improved interaction quality if behavioral changes are not carefully managed [7].

3.2 Autonomy and User Control

Assistive systems are often designed to act proactively in order to reduce user effort. While proactive behavior can be beneficial, it can also conflict with users' desire to remain in control of their actions and environment [18]. Fully autonomous behavior risks disempowering users, particularly when system decisions are difficult to anticipate or override [27].

Rather than treating autonomy as a fixed system property, assistive interaction suggests the need for autonomy to be negotiated dynamically through interaction [8].

3.3 Personalization and Transparency

Personalization relies on learning from user behavior and preferences. However, learning processes are often opaque, and their effects on system behavior may be difficult for users to understand [22]. In assistive contexts, limited transparency can undermine trust and lead to reduced system acceptance [30].

This tension underscores the importance of making personalization processes observable and interpretable at the interaction level.

3.4 Illustrative Scenario

Consider an assistive mobile robot supporting a user in a domestic environment. Initially, the system waits for explicit commands before retrieving objects. Over time, it learns frequent patterns and begins to proactively suggest actions. If such proactive behavior is introduced without signaling the change, users may experience reduced predictability and diminished control [13]. However, if the system announces increased initiative, allows easy override, and provides visible cues about its reasoning, autonomy becomes a negotiated property rather than an imposed one [26].

This example illustrates how adaptivity, predictability, and autonomy intersect in practice.

4 Design Implications for Interacting with Assistive AI

Based on these interactional tensions, several design implications can be derived for adaptive AI systems intended for assistive contexts.

Contextual Intelligibility Assistive systems should make its actions and assumptions intelligible in relation to the current interaction context. Rather than providing global explanations, systems should communicate intent, uncertainty, or limitations when they become relevant for user decision-making [21].

Negotiated Autonomy Autonomy should not be treated as a static system property but as a dynamic interactional variable [20]. Negotiated autonomy can be operationalized by mechanisms such as: Explicit autonomy levels selectable by the user, context-dependent autonomy shifts that are announced before execution, confirmation requirements for safety-critical actions, and interaction histories that inform gradual increases or decreases in system initiative. Such mechanisms allow autonomy to be adjusted transparently over time while preserving user control. The goal is not to maximize automation but to align system initiative with user expectations and situational demands.

Stability-Oriented Adaptation Adaptation should be introduced gradually and conservatively. Changes in system behavior should preserve interactional continuity and avoid disrupting established routines. In assistive contexts, maintaining consistent interaction patterns can be more important than maximizing short-term performance.

Reinforcement of User Agency Assistive AI systems should augment user capabilities rather than replace user decision-making. System behavior should be designed to support user competence, awareness, and involvement, even when automation is technically feasible.

5 Open Research Questions

Viewing assistive HRI as a reference domain raises several research questions for adaptive and interactive AI systems:

- How can adaptive systems balance responsiveness with interactional stability?
- Which interaction mechanisms support the dynamic negotiation of autonomy?
- How can long-term human-AI interaction be evaluated beyond short-term usability or performance metrics?
- How does physical embodiment influence users' perception of agency, responsibility, and trust?

6 Conclusion

Assistive Human-Robot Interaction exposes interactional constraints that are central to adaptive AI systems [1]. Long-term use, contextual variability, and safety relevance require careful coordination of adaptivity, autonomy, and transparency [5]. By foregrounding interactional stability and negotiated autonomy, assistive contexts provide a structured lens for examining fundamental questions of human–AI interaction.

These considerations align directly with the workshop's focus on human-centered robotics and interactive AI. We aim to contribute to a discussion on how adaptive systems can remain controllable, interpretable, and suitable for sustained real-world deployment.

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