Forefeel the Move: Investigating Proprioceptive Feedback for Communicating Imminent Motions of Body-actuating Systems

Marie Muehlhaus
Saarland University,
Saarland Informatics Campus
Saarbrücken, Germany
muehlhaus@cs.uni-saarland.de

Martin Schmitz
University of Koblenz
Koblenz, Germany
martin@uni-koblenz.de

Jürgen Steimle
Saarland University,
Saarland Informatics Campus
Saarbrücken, Germany
steimle@cs.uni-saarland.de

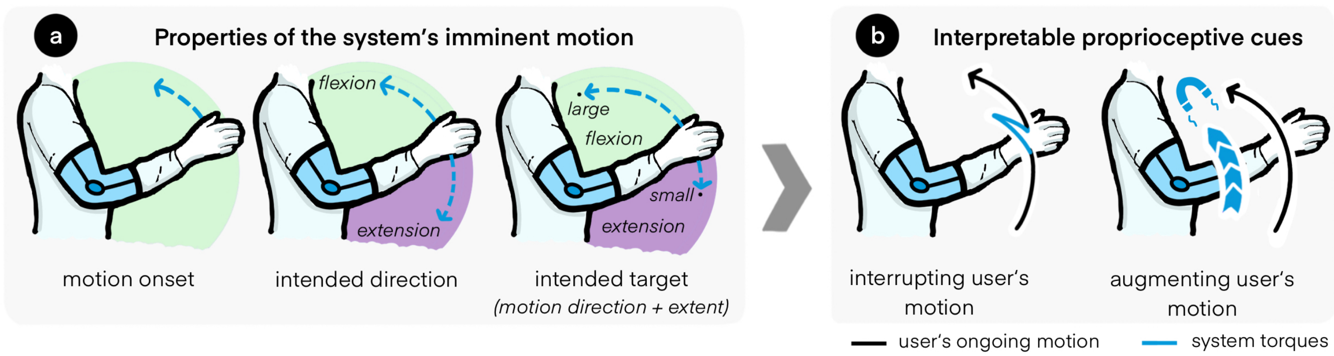

Figure 1: Unexpected body actuation introduces critical challenges. In this work, we (a) focus on three key motion properties of body-actuating systems that could be conveyed to users prior to actuation, and (b) compare variations of different proprioceptive cues that communicate these properties either by interrupting or augmenting ongoing user motion with additional torques.

Abstract

Systems actuating the body can proactively assist users in diverse tasks. However, unexpected body actuation may pose safety risks. We propose proprioceptive feedback to inform users about an imminent actuation before the system takes control. In a user study, we compare different proprioceptive cues that either interrupt or augment user motion to convey (1) solely that a body actuation is imminent, (2) its direction, or (3) its target. To enable a controlled investigation, we confined the cues to one degree-of-freedom joints and implemented them in an elbow exoskeleton. The results show that all cues are highly noticeable, offering an integrated feedback channel; yet, their effectiveness in communicating direction and target differed: While cues that augmented user motion were more accurate and preferred, disruptive cues enabled faster but less accurate interpretations. Furthermore, our analysis revealed that proprioceptive feedback enhanced the expressiveness of the conveyed information and user's aspirations for adaptive feedback.

CCS Concepts

• **Human-centered computing** → *Interaction techniques*; *Empirical studies in HCI*; Haptic devices.

Keywords

Wearables; body actuation; proprioception; motion; intent.

ACM Reference Format:
Marie Muehlhaus, Martin Schmitz, and Jürgen Steimle. 2026. Forefeel the Move: Investigating Proprioceptive Feedback for Communicating Imminent Motions of Body-actuating Systems . In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3772318.3790487

ACM ISBN 979-8-4007-2278-3/2026/04
https://doi.org/10.1145/3772318.3790487

1 Introduction

Systems that physically actuate the human body, like electrical muscle stimulation [63, 80] or exoskeletons [55, 83], are gaining attention in HCI for their potential to enhance physical abilities. For instance, they can assist in physically demanding tasks [6], support motor learning [85] or aid activities of daily life [37].

But while these systems are traditionally expected to follow user intentions, there is also a need for mixed-initiative interactions, where both user and system proactively initiate actions, enabling systems to act more like partners [33]. System-initiated actuation can occur in various situations and ways: For instance, brief system interventions may prevent hazards unknown to the user, like adjusting lifting posture when sensors detect an obstacle while the user carries a box downstairs to avoid collision. Beyond safety, systems may support movement when assistance is needed, such as correcting unergonomic postures or guiding sports movements (e.g., golfing [58]) after repeated failed user attempts. In extreme cases, they may take full control, e.g., to improve task efficiency [59] or complement user expertise [32].

However, system-initiated actuation may surprise users or conflict with their intentions. To prevent such mismatches, systems should inform users about their intention to move (or *motion intent*). We envision that communicating motion intent prior to actuation helps users build expectation, assess its appropriateness and intervene if needed, preserving a sense of control over their body. Yet, little is known about conveying imminent motions in body-actuating systems.

Unlike visual and auditory strategies for conveying intent in off-body robots [25, 52, 60], haptic feedback suits environments where these channels are unavailable or overloaded, such as in noisy or visually cluttered settings [71]. For body-actuating systems, proprioceptive feedback, a haptic modality resulting from physical movement of the limbs [47], is particularly interesting for conveying intent: It aligns with the natural feedback capabilities of body-actuating systems and delivers the information directly to the affected body part. Yet, proprioceptive feedback remains underexplored, and we lack a principled understanding of its effectiveness for communicating motion intent.

In this paper, we contribute insights from a mixed-methods study investigating the potential of proprioceptive feedback to communicate motion intent of body-actuating systems. The study focuses on three properties of motion intent critical for body-actuating systems: They either inform the user (1) only *that* an actuation is imminent, or provide additional information about (2) its *direction* or (3) its *target*. For each property, we designed brief proprioceptive cues informing the user about the imminent actuation based on distinct strategies that either interrupt or enhance ongoing user movement (see Figure 1). To provide a controlled yet representative case for a principled investigation, we investigated those cues in one degree-of-freedom (DoF) motions of hinge joints capable of flexion and extension and implemented them in a proof-of-concept elbow exoskeleton. The exoskeleton was chosen for its precise control over relevant parameters while requiring minimal calibration, and the elbow for its relevance in everyday activities [24].

For each property, we assessed how quickly, accurately, and confidently users interpreted the cues and gathered qualitative insights from interviews. Results reveal that all proprioceptive cues have high noticeability, yet varied in their effectiveness of conveying intent: interruptive cues were fastest to interpret, while those augmenting motion were interpreted more accurately and confidently and integrated more seamlessly with the user activity, making them the preferred user choice. Qualitative feedback shows users' desire for adaptive, personalized cues and suggests that the proprioceptive cues differ in their perceived urgency and add an affective layer of interpretation. We contextualize these findings by comparing them to prior studies that have assessed the effectiveness of distinct feedback modalities.

In summary, this paper makes the following contributions:

- We propose proprioceptive feedback as an embodied means to convey motion intent of body-actuating systems.
- We designed interpretable proprioceptive cues for 1 DoF hinge joints and implemented them in an elbow exoskeleton. The cues either inform the user about the intended motion onset, direction or target.
- Results show that interruptive cues were interpreted fastest, while augmenting cues yielded higher accuracy, confidence, and seamless integration. We discuss the trade-off between response time and interpretation accuracy, users' aspirations for adaptive feedback, and the affective dimension of body-actuating systems.

2 Related Work

Our work is motivated by the growing interest in body-actuating systems, the need for interpretable behavior, and research on wearable output modalities in HCI.

2.1 Body-actuating Systems

Prior work explores diverse approaches to actuating the body. One approach is Electrical Muscle Stimulation (EMS), which induces muscle contractions to actuate the body (e.g., [30, 80]). Magnetic Muscle Stimulation and Transcranial Magnetic Stimulation have recently emerged as alternatives using magnetic stimulation [81, 82]. Exoskeletons represent a non-invasive form of body actuation through external structures which apply forces directly to the limbs using, e.g., motor-driven [26, 55], pneumatic [27] or hydraulic [22] actuation. Alternatively, string-based systems actuate the body by pulling strings attached to the user and can be powered via body-worn motors [15, 23], stationary cage-like structures [68], or mobile devices such as drones [34]. Other systems actuate the body through handheld devices using techniques such as air propulsion [31] or flywheel-based torque cues [91]. These body-actuating systems have a wide range of applications, from personal contexts such as gaming [83, 86], navigation [63] and skill acquisition [85], to more professional contexts in industry [6] and rehabilitation [65]. However, the systems can also pose usability and safety risks when actuation occurs unexpectedly [50] or misaligns with user intentions, impacting users' sense of agency [39]. Hence, this paper explores methods to inform users of imminent body actuation before the action takes place.

2.2 Interpretability of Actuated Systems

When interacting with a system, it is essential for users to understand what actions they can perform and to anticipate those the system may take. The former is supported through *feedforward* interactions, which show the user the available actions and outcomes [56, 84], the latter through *intent communication*. Here, the system communicates its own forthcoming actions to the user to enhance interpretability. Intent communication has primarily been applied in physical domains, such as in autonomous driving, where takeover requests may include contextual cues for safer handover of control [46], and robotics, where robots convey intended targets or trajectories to align user expectations [9, 61] and improve safety, interaction quality, and efficiency [5, 17, 78]. Since body-actuating systems directly affect the user's body and surroundings, and users often have limited time to prepare in case of system-initiated actuation, communicating system intent is critical. Prior work proposed different concepts for evaluating a system's interpretability [9], distinguishing cases where users know the system's goals from those where they do not. The latter is most relevant here, as users may lack awareness when actuation occurs unexpectedly. A key concept in this context is *legibility*, describing a system's ability to quickly and clearly convey its intended motion to users [16, 18]. Informed by this notion, we assess the proposed proprioceptive cues based on how quickly and accurately users interpret them.

2.3 Wearable Output Modalities

Prior work has explored diverse feedback modalities for delivering notifications in a wearable form factor, including visual, auditory, and haptic feedback (e.g., [4, 67, 74, 88]). Haptic feedback has emerged as a promising modality as it allows for eyes- and ears-free interaction and can complement or replace other modalities when those channels are occupied. Leveraging the body as a feedback channel, these *embodied* notifications [71] enable direct, targeted communication. Beyond communicating *that* something is happening, prior work also used haptic feedback to encode semantic information. For instance, cutaneous cues may provide directional information to support motor learning [54], navigation [28], posture correction [73] or inform users about actions of their prosthesis [76]. Proprioceptive feedback, referring to the body's ability to sense the position, orientation, and movement of limbs, joints, and muscles [70], offers an alternative channel, e.g., for delivering notifications [8], take-over requests in autonomous vehicles [21], or for conveying spatial or temporal information for obstacle avoidance [72], motion guidance [11], or prosthetics [1]. However, proprioceptive feedback remains underexplored compared to other haptic modalities and has not yet been considered for intent communication. We address this gap by comparing techniques for conveying motion intent of body-actuating systems via proprioceptive feedback and relate our findings to prior work on wearable output modalities.

3 Approach

Unexpected body actuation may impact user experience and safety [50, 57]. Thus, we posit that body-actuating systems should inform users about an imminent actuation and relevant details to help users build expectation.

We propose proprioceptive feedback to convey such motion intent, as it can seamlessly integrate with the motion apparatus, provides a low-friction channel for embodied notifications, and also allows to encode more specific properties of an upcoming motion. Furthermore, it does not interfere with sensory channels required for the primary task and works in noisy or visually cluttered environments. We provide this feedback directly at the locus of interaction, i.e., where the actuation occurs. Such localized feedback lets users *forefeel* imminent actuation at the affected body part, easing direct mapping and interpretation of information compared to feedback relocated to other body parts. This can be especially beneficial when multiple body parts are augmented, preventing perceptual overlap and preserving intuitive mapping.

In the following, we first establish fundamental motion properties to convey in body-actuating systems, then derive different proprioceptive cues for each property, tailored to one degree-of-freedom (DoF) hinge joints with flexion and extension capabilities. We then present a prototypical implementation using an elbow exoskeleton.

3.1 Conveying Fundamental Properties of Motion

Informed by the properties of motion intent considered in prior work (e.g., [41, 44, 52, 61]), this paper focuses on three properties that are particularly relevant for body actuation. They build on each other, from just communicating that the system intends to actuate the body, to also communicating the extent and direction of that imminent body actuation.

The **onset of a motion** is the most fundamental information, simply signaling that a body actuation is about to happen. It is implicitly included whenever a system expresses any motion intent prior to carrying out the motion.

Second, it is also important to inform the user of the specific **intended direction** in which the system wants to move. While direction is frequently employed as an important property of motion intent, e.g., for mobile robots [51, 52, 79] or humanoids [52], it is particularly relevant for body-actuating systems as torques applied in unintended directions can cause injuries [57]. For body-actuating systems, direction of motion can be naturally defined relative to the current position of the body. For 1 DoF hinge joints, this is either towards flexion or extension.

Conveying the **intended target** of a motion has been extensively researched in human-robot interaction literature, e.g., [16, 41, 78, 87], but remains an open challenge for body-actuating systems. Similarly to a direction intent, we define the target as relative to the body, rather than in 3D world coordinates, and decompose it into (1) the *direction* of the target and (2) the *extent* of motion required to reach the target relative to the user's body. Hence, the system informs the user how far in a specific direction it intends to move. Communicating the motion extent is particularly relevant for body-actuating systems to prevent hazardous situations where ergonomic and safe kinematic limits may be exceeded [50].

3.2 Interpretable Proprioceptive Cues

For each motion property, we propose different proprioceptive cues that seamlessly blend with the user's motion to convey the respective information prior to system actuation. Fundamentally, we distinguish between cues that interrupt a user's motion for the duration of the cue (see Figure 2a) – standalone, as traditional notifications often are – and cues that augment it by applying additional torques (see Figure 2b and c) – like a dance instructor guiding posture.

We first conducted an open-ended brainstorming phase to generate a broad set of candidate cues for each motion property, which we refined into a smaller set of fundamental variants. We then systematically altered these variants by fine-tuning and user testing key physical parameters (e.g., speed and angular displacement). In the following, we describe the proprioceptive cues and outline their underlying parameters.

3.2.1 Conveying the onset of an imminent motion. For body-actuating systems that intend to communicate only the motion onset, we propose three proprioceptive cues (see Figure 2):

The **interrupt cue** disrupts a user's ongoing motion through a brief bidirectional forth-and-back motion that draws the user's attention. It is one of the most basic motions achievable in a 1 DoF

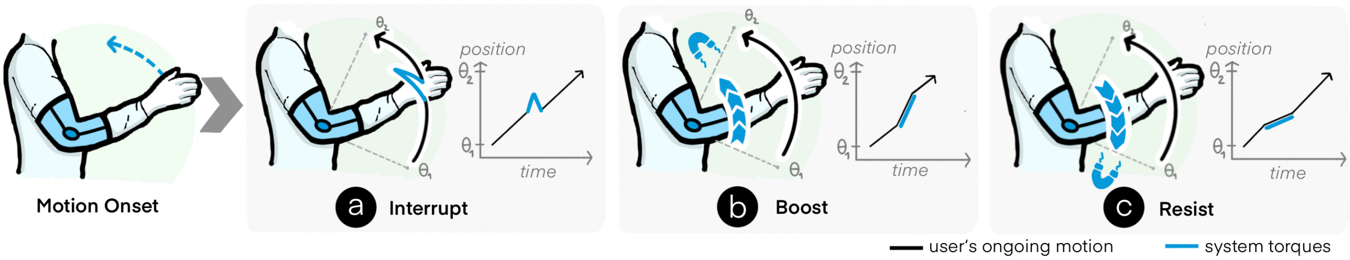

Figure 2: We propose three proprioceptive cues to inform the user about the imminent onset of a motion. They either (a) briefly interrupt an ongoing user motion, (b) boost it by applying torques in the user's motion direction, or (c) resist it through opposing torques.

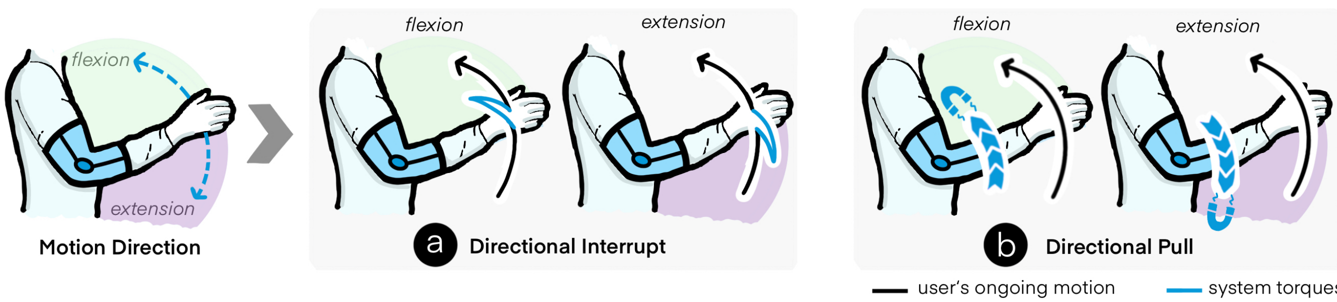

Figure 3: We propose two proprioceptive cues to inform the user about the direction (flexion or extension) of an imminent body actuation. The cues (a) either interrupt an ongoing user motion or (b) augment it through a directed pulling torque.

joint and its symbolic motion loosely resembles twitching, a metaphor of nervousness or waking up. A similar approach has been taken as a visual means to convey a humanoid's motion intent [44] and for delivering proprioceptive notifications at the finger [8]. For this proprioceptive cue, the speed and angular displacement of the induced motion are two important parameters that must be selected so that they are clearly perceptible but have only a minimal impact on ongoing user activity.

The **boost cue** briefly speeds up the user's ongoing motion, applying a constant and gentle torque aligned with the user's movement path. This means that rather than fully interrupting, the system temporarily modifies the user motion.

In contrast to boosting, the **resist cue** applies a torque in the opposite direction of the user motion, slowing it down. Both cues must be strong and sustained enough to be noticeable yet weak and brief enough to avoid interfering with the user's inherent motion.

3.2.2 Conveying the direction of an imminent motion. We extend the previous cues to convey direction (see Figure 3):

The **directional interrupt** cue extends the interrupt cue by operationalizing the direction of the forth-and-back motion to convey the direction of the imminent motion: First, the system briefly pushes the limb forward in the intended direction and then pulls it back in the opposite direction. This creates a direct mapping between the direction in which the cue pushes the arm and the system's intended motion direction. The angular displacement and speed are key factors to allow the user to discern the direction while minimizing the interference with their own motion.

The **directional pull** cue combines boosting and resisting through a torque applied only in the direction of the imminent motion. Consequently, the system either boosts the user's inherent motion when the user is already moving in the intended direction or resists it in all other directions. Conceptually, this is related to the push/pull metaphors of saltatory vibration patterns to convey directionality (e.g., [28, 48, 54]). The selected torque must be strong and sustained enough for users to explore and process the direction of the torque, yet weak enough to preserve user control.

3.2.3 Conveying the target of an imminent motion. We extend the previous cues to convey not only the direction but also the extent of the imminent motion. Figure 4 depicts the proprioceptive cues.

The **targeted interrupt** cue builds on the directional interrupt cue by mapping the extent of the directional forth-and-back motion to the extent of the imminent body actuation: It conveys a smaller motion extent through a small physical displacement of the limb in the intended direction and increases the displacement to signal a larger motion.

In contrast, the **targeted pull** cue encodes the motion extent by varying the magnitude of the torque: higher torques inform the user about an imminent actuation with a larger extent, while lower torques imply a smaller extent. This aligns with previous studies mapping the stimulus intensity to spatial or temporal distances (e.g., [43, 72]).

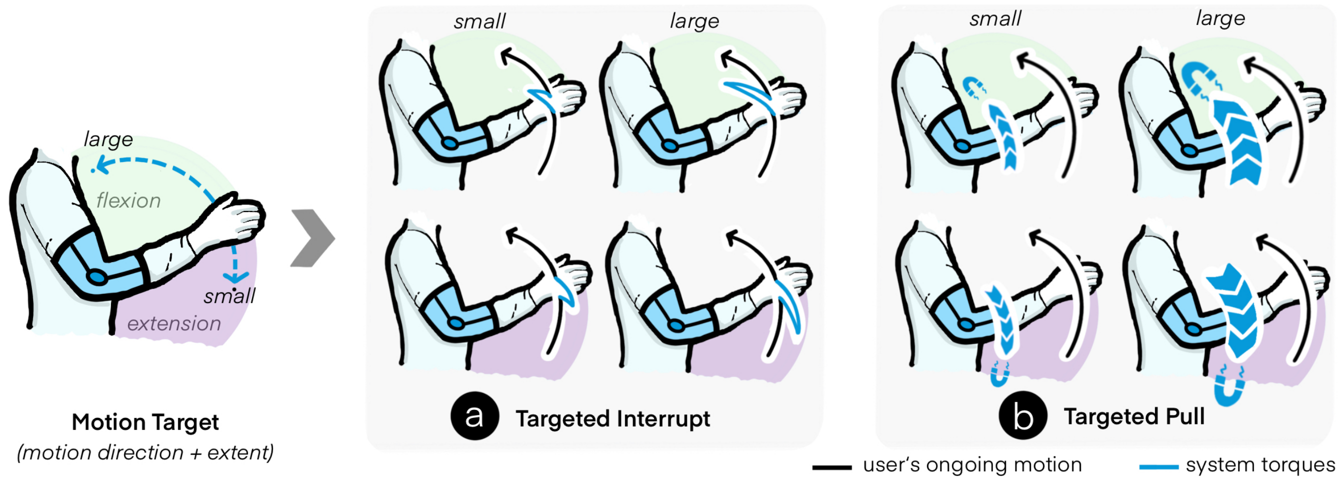

Figure 4: The motion target is composed of the motion direction (flexion or extension) and extent (small to large). We propose two proprioceptive cues to convey the intended target: (a) either interrupting a user motion or (b) augmenting it through a pulling torque.

3.3 Prototypical Implementation

The proposed proprioceptive cues are applicable to any technology that can actuate the body with controllable torques, speed and displacements. For our study, we prototypically implemented them in an elbow exoskeleton, supporting the simple actions of flexing and extending the joint. The prototype builds on the EduExo Maker[1], which we modified to include a stronger motor (Dynamixel XM430-W210-T, 3 N.m, 12 V). The motor is controlled via an OpenRB-150 microcontroller. Implementing the proprioceptive cues requires calibration of their physical parameters to match the context of use since perceptual thresholds can vary with the user's motion speed [29, 40]. We detail on the study setting which informed the selection of parameters (cf., Table 1) in the next section. The exoskeleton is depicted in Figure 5.

4 User Study

We employed a mixed-methods study [13] to explore the potential of proprioceptive cues for conveying a system's intent to actuate the body. The mixed-methods approach enabled us to collect quantitative measures to objectively assess the cues' effectiveness in conveying intent, while qualitative data from think-aloud protocols and interviews captured users' subjective experiences. These objectives are articulated through two research questions (RQs):

RQ1: How do the proposed cues quantitatively affect noticeability and interpretability?
RQ2: How do the different cues qualitatively affect users' preferences and experiences of interpreting them?

RQ1 and RQ2 lead to the final mixed-methods research question (cf. [13]):

RQ3: What implications for the design of proprioceptive cues emerge from combining the outcomes of the quantitative performance data with the qualitative data about user experience?

[1]EduExo Maker: https://www.auxivo.com/eduexo-maker, last accessed 06/10/2025

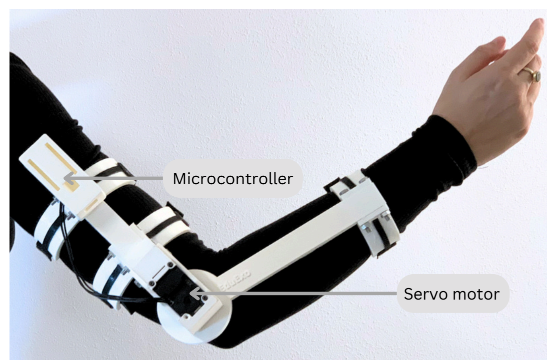

Figure 5: The elbow exoskeleton used to implement the interpretable proprioceptive cues.

4.1 Apparatus

To implement the proprioceptive cues described in Section 3.2, we calibrated the physical parameters through pre-tests with adult participants (2f, 2m, 0d). Participants systematically evaluated combinations of torque, velocity, and displacement for comfort, detectability, and preference. The final parameters were those rated as both comfortable and reliably detectable and can be found in Table 1. The pre-tests and the main study were conducted under identical conditions. A Processing application guided participants through the tasks, logged data, and controlled the prototype.

4.2 Design & Tasks

The study followed a within-subjects design. For each motion property (motion onset, direction, target), we compare the proprioceptive cues regarding their noticeability and interpretability.

To study proprioceptive cues in a realistic setting, participants performed upper limb workout tasks using the exoskeleton. The device first demonstrated a motion sequence by actuating the user's

Property	Cue	Displacement (deg)	Speed ($\frac{deg}{sec}$)	Cue	Torque (N.m)	Duration (sec)
Onset	*Interrupt*	5 forth + 5 back	100 forth + 100 back	*Boost*	0.14 in user's motion direction	0.8
				Resist	0.14 opposed to user motion	0.8
Direction	*Directional Interrupt*	15 in intended direction + 15 back	100 in intended direction + 20 back for pronounced effect	*Directional Pull*	0.14 in intended direction	3
Target	*Targeted Interrupt*	10 + 10 (small), 20 + 20 (large)	100 + 20 (both)	*Targeted Pull*	0.12 (small); 0.24 (large) in intended direction	3

Table 1: An overview of the parameters used to realize the proposed proprioceptive cues in an elbow exoskeleton. All variations of *Interrupt* were realized with the motor's maximum torque. The parameter selection was informed by pre-tests with users.

arm accordingly, then let users practice it independently. After a random interval, but no later than 20 seconds, it resumed control to show the next motion, signaling this intent through our proprioceptive cues. Participants pressed a button as soon as they detected and interpreted the intent conveyed by the cue, then completed an on-screen questionnaire about their interpretation and confidence. The demonstrated motion sequence is randomly chosen from four options, each involving repetitive elbow flexion and extension. The options differ in direction (starting with either elbow flexion or extension) and in motion extent, either covering 50% or 100% of the user's full motion span.

We split the study into three tasks, each focusing on one property of motion. To mitigate order effects between tasks, their order was counterbalanced with a Latin square. Within a task, we presented participants with the respective proprioceptive cues in a randomized order (see Figure 6).

4.2.1 Task 1: Understanding the onset of an imminent motion. The participant is presented with proprioceptive cues that only inform them *that* the exoskeleton intends to soon take over to demonstrate the next motion sequence. Hence, the participant's task is to press a button as soon as they perceive the cue.

In this task, we vary Motion Onset Cue as an independent variable with three levels: Interrupt, Boost, Resist (see Section 3.2.1). We used the following dependent variables to assess how quickly and clearly the cues can be understood:

- Detection accuracy (in %): The percentage of trials for which the participant correctly detected the cue. For each trial, we logged whether the participant correctly pressed a button after the cue occurred. A trial was counted as a miss if the button was pressed either before the cue occurred or too late (timeout after 10 seconds).
- Detection confidence: For each detected cue, we asked participants to rate their confidence in having correctly detected it on a 7-point Likert Scale[2].
- Response time (in sec): We logged the time from the presentation of the cue to the participant pressing the button.

4.2.2 Task 2: Understanding the direction of an imminent motion. The participant is presented with proprioceptive cues that convey the system's intended motion direction. Hence, the participant's task is to press a button as soon as they interpreted the cue and indicate in a questionnaire whether they think the next motion will start either with elbow *flexion* or *extension.*

In this task, we vary Motion Direction Cue as an independent variable with two levels: Directional interrupt and Directional pull (see Section 3.2.2). In addition to evaluating how well users noticed the stimulus, it is also important to understand how effectively they interpreted the information it conveyed. Therefore, we used the following dependent variables to assess both the noticeability of the cue and the interpretability of the directional information:

- Detection accuracy, detection confidence, response time: Analogous to Task 1.
- Interpretation accuracy (in %): The percentage of trials that the participant correctly interpreted the direction.
- Interpretation confidence: After each detected trial, participants rated their confidence in having correctly interpreted the direction on a 7-point Likert Scale [2].

4.2.3 Task 3: Understanding the target of an imminent motion. The participants are presented with proprioceptive cues that convey the intended target. Hence, in addition to whether the upcoming motion will be a *flexion* or *extension* (direction), they also interpret whether it will be *small* or *large* (extent). While the cues could, in principle, convey continuous information about motion extent, we discretized the extent into two levels. This allowed for a focused calibration of parameters encoding the small and large motion extent, which becomes increasingly complex with finer granularity.

We vary Motion Target Cue as an independent variable with two levels: Targeted interrupt and Targeted pull (see Section 3.2.3). We can build on the measures of Task 1 and 2 and use the following dependent variables to assess the noticeability and interpretability of the cues:

- Detection accuracy, detection confidence, response time: Analogous to Task 1.
- Interpretation accuracy (in %): The percentage of trials for which the participant has correctly interpreted both the direction and motion extent conveyed by the cue.
- Interpretation confidences: This measure holds two items on a 7-point Likert Scale [2]: After each detected trial, participants rated (1) their confidence in having correctly interpreted the motion extent and (2) their confidence in having correctly interpreted the motion direction.

[2]1: no confidence, 7: full confidence

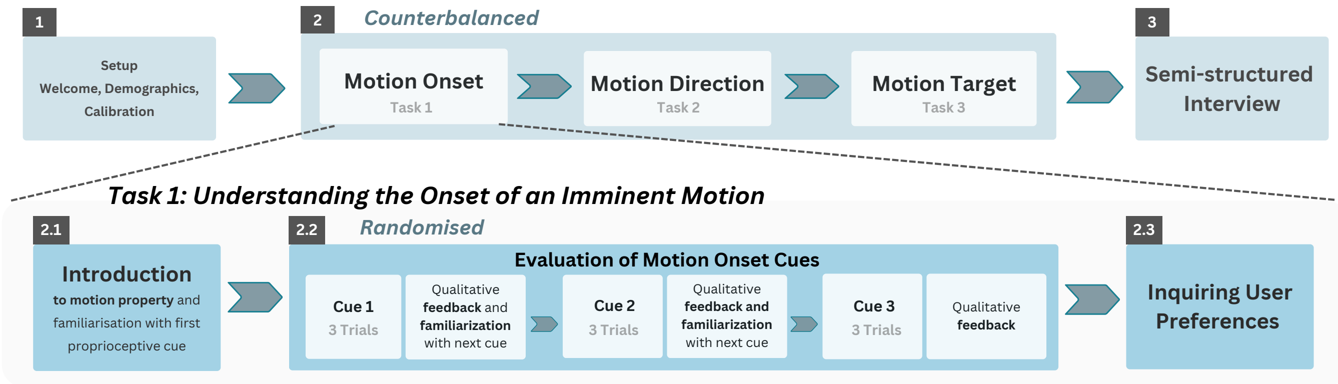

Figure 6: The study consists of three tasks, each corresponding to one property of the system's imminent motion. For each task, we varied the proprioceptive cue as an independent variable. The order of tasks was counterbalanced, the order of cues randomized.

4.3 Procedure

The study took place in a quiet environment, while the participant was seated at a table. Figure 6 illustrates the procedure. After collecting informed consent and demographics, the experimenter calibrated the exoskeleton to the participant's comfortable range of motion and familiarized them with the task of the physical workout (step 1).

The experimenter then introduced the participant to the property of motion that will be conveyed as part of the task (either the motion onset, direction, or target) and the first proprioceptive cue. In an initial learning phase, the participants familiarized themselves with the cue until they felt confident in interpreting the conveyed information (step 2.1). Next, three consecutive trials were conducted where participants pressed a button upon detecting and interpreting the cue and logged their answers in a questionnaire. Afterwards, participants described their experience with the cue. This was repeated for all cues of the current task (step 2.2). Once all proprioceptive cues of a task were evaluated, participants ranked the cues by preference (step 2.3). Steps 2.1–2.3 were repeated for all three tasks. All throughout, the participants were encouraged to think aloud.

The study finished with a semi-structured interview to gather feedback on the noticeability and interpretability of the cues and understand factors that influenced participants' experiences (step 3). Each study session took 90–120 minutes and was audio-recorded. The study was approved by the university's ethical review board (no. 23-07-6).

4.4 Participants

We recruited 12 participants (6f, 6m, 0d; M = 26 y; SD = 3.4 y) from various cultural backgrounds (Europe, Middle East, Eastern Asia) and educational levels (Bachelor, Master, PhD, PostDocs), with backgrounds in HCI, robotics, haptics, and cognitive science. Eleven participants were right-handed, one left-handed; all wore the exoskeleton on the right arm. Prior work shows similar joint position sense in both arms [42], indicating no bias due to handedness. None reported any physical or neurological condition that would have affected their arm's motion or proprioception.

4.5 Data Analysis

For the quantitative data, we first assessed the assumption of normality using QQplots. In case of violated normality and for the ordinal Likert items, we apply the Friedman test for Task 1, as it is suited for IVs with more than two levels. For significant results, we follow up with pairwise Wilcoxon signed-rank tests. We report Kendall's W as the measure of the effect size. For Task 2 & 3, which both have IVs with two levels, we directly apply the Wilcoxon signed-rank test and report rank-biserial r as the measure of the effect size. For both, rank-biserial r and Kendall's W, we use the suggestions by Cohen [12] to classify them as small (>.10), medium (>.30), or large (>.50). For parametric data, we apply a one-way RM ANOVA for Task 1 and applied Bonferroni-corrected t-tests for post-hoc analysis; we report the generalized ETA squared η_g^2 as the measure of the effect size (small: > .01, medium: > .06, large: > .14). For Task 2 & 3, we directly apply the t-tests and report Cohen's d as the measure of the effect size (small: > .20, medium: > .50, large: > .80).

We analyzed the qualitative data inductively. After transcribing participants' statements, we conducted a qualitative content analysis (QCA) [53] with an objective focus on the cues' detectability, interpretability, and integration in the user's ongoing motions and a thematic analysis [7] to identify themes related to participants' experiences across cues.

5 Results

We present the results of the experiment structured around the three tasks, followed by a performance comparison across tasks and an analysis of the final interview.

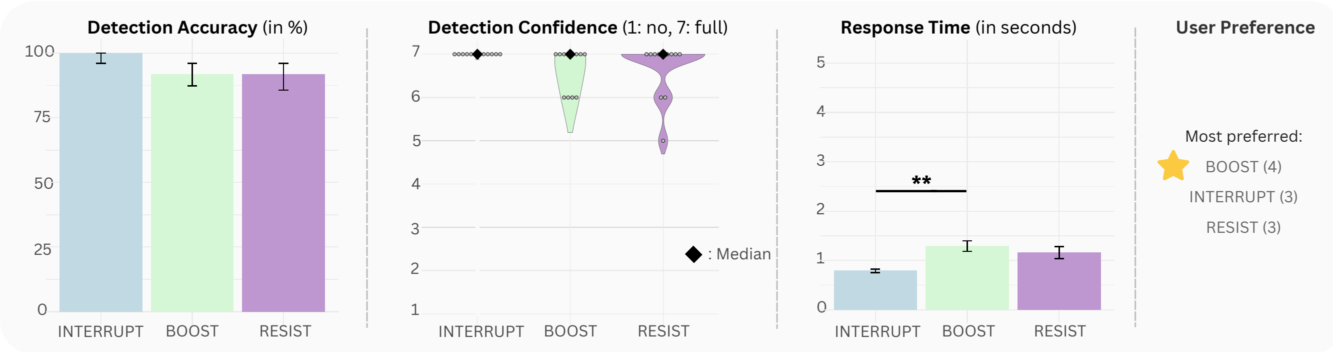

Figure 7: Results of Task 1 show that participants confidently detected all three proprioceptive cues with a high accuracy above 90% and low response times and expressed a slight preference for Boost. All error bars depict the standard error.

5.1 Task 1: Understanding the Onset of an Imminent Motion

Task 1 sought to compare three levels of Motion Onset Cue (Interrupt, Boost, and Resist) for conveying the onset of an imminent motion. Figure 7 provides an overview of the quantitative results.

Detection accuracy. The analysis shows that Interrupt yielded the highest mean detection accuracy (μ = 100.0%, σ = 0%), with no missed trials. Boost and Resist perform almost equally (μ = 91.7%, σ = 15.1% vs. μ = 91.7%, σ = 20.7%). We did not find a significant effect of Motion Onset Cue (χ^2 (2) = 2.8, p > .05) on the detection accuracy.

Detection confidence. We analyzed the self-reported detection confidences on a 7-point Likert scale (from 1 meaning no confidence to 7 meaning full confidence). Participants reported a very high median of $\tilde{x}$ = 7 with a median absolute deviation (MAD) of 0 for all cues, indicating that all cues could be confidently detected. Unsurprisingly, we did not find a significant (χ^2 (2) = 4.6, p > .05) effect.

Response time. The results show that Interrupt yielded the lowest mean response time (μ = 0.8s, σ = 0.3s), followed by Resist (μ = 1.2s, σ = 0.7s) and Boost (μ = 1.3s, σ = 0.6s). The analysis reveals a significant effect ($F_{2,22}$ = 8.00, p < .005) with a medium (η_g^2 = 0.13) effect size. Post-hoc tests revealed a significantly lower response time for Interrupt compared to Boost ($t(11)$ = 4.08, p < .01).

User preferences. When asked about preferences, there was no clear trend for any proprioceptive cue: Boost was first-ranked by four participants and Resist and Interrupt by three participants each. However, with eight participants, Resist was most frequently ranked last, while Boost was last-ranked by two and Interrupt by only one participant.

Subjective feedback. Here, we report the results of the QCA, reflecting participants' opinions of each cue:

Participants found that Interrupt is easy to detect (n=6), requires low focus (n=2), enables fast reactions (n=2) and *"[b]etween these three [cues], I felt it is most expressive"* (P9). However, participants also noted that Interrupt *"might cause you to just fail the thing that you are trying to do"*, highlighting its rather disruptive nature.

Contrarily, many participants stated that Boost integrated well with their motions (n=6), as it feels natural (n=3), subtle (n=5), and *"rewards the movements I'm doing instead of interrupting"* (P10). But the almost seamless integration with the participant's motion also increased the difficulty (n=9) and time (n=3) required to detect *"that actually the robot is moving your arm instead of yourself"* (P2). P5 added that they would *"prefer the smoother, more subtle interactions that [...] get more intense if I'm ignoring them"*, addressing the trade-off between good noticeability and integration.

Finally, for Resist, participants positively stated that the cue was easy to detect (n=5) and described it as natural (n=2) and familiar (n=2). However, other participants were less positive as it would be a more intense way of conveying intent, which less seamlessly integrates into the participants' ongoing motion (n=4): While *"it feels still comfortable to ignore or slightly overcome [the torque]"* (P8), others mentioned that *"it kind of feels like I have to work against it"* (P10).

5.2 Task 2: Understanding the Direction of an Imminent Motion

In Task 2, we compared two levels of Motion Direction Cue (Interrupt, Pull) for conveying the direction of an imminent body actuation, either moving towards *flexion* or *extension.* Figure 8 provides an overview of the results.

Detection accuracy. Directional interrupt yielded a very high detection accuracy of μ = 97.2%, σ = 9.6%. All instances of Directional pull have been detected (μ = 100%, σ = 0%). Unsurprisingly, the analysis did not reveal significant effects of Motion Direction Cue (V = 1, p > .05) on the detection accuracy.

Detection confidence. Further, participants reported a very high detection confidence for both cues ($\tilde{x}$ = 7, MAD = 0), indicating that they can be confidently detected. Hence, we also did not find a significant (V = 0, p > .05) effect.

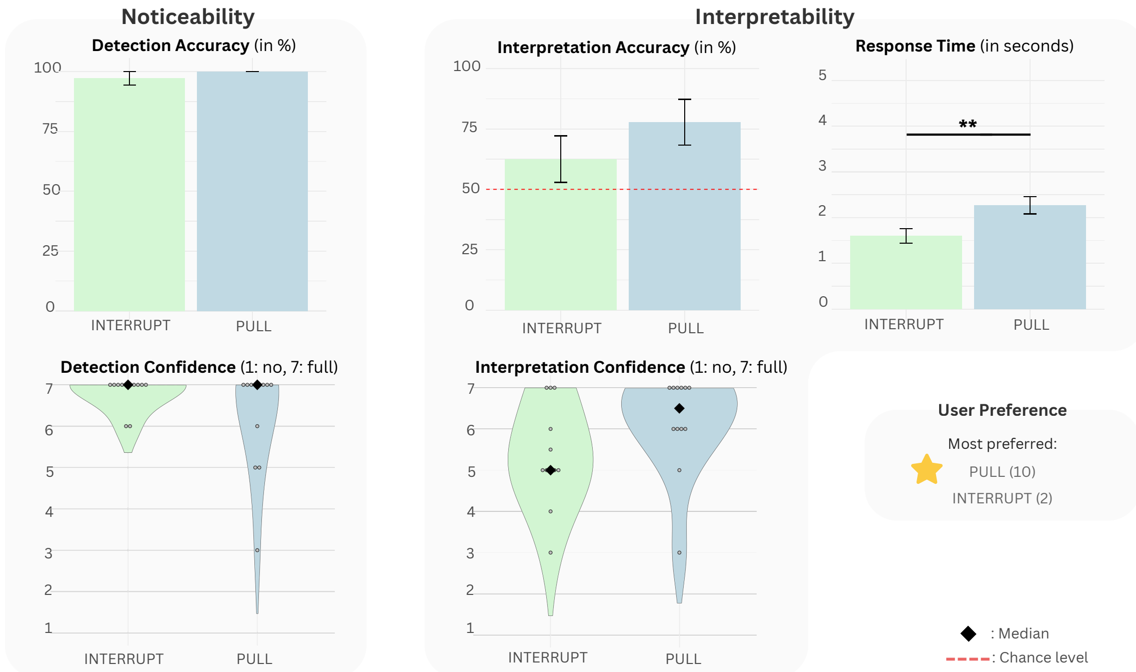

Figure 8: Results of Task 2 show that participants could confidently detect both proprioceptive cues with a high accuracy above 90%, while Directional pull yielded better interpretability and was more preferred. All error bars depict the standard error.

Response time. The analysis revealed significantly ($t(11) = 4.02$, $p < .005$) faster response times for Directional interrupt ($\mu = 1.6s$, $\sigma = 0.9s$) compared to Directional pull ($\mu = 2.3s$, $\sigma = 1.1s$) with a large ($d = 1.2.$) effect size.

Interpretation accuracy. Beyond accurately detecting an imminent motion at all, we also assessed whether participants correctly interpreted the intended direction. The results show that Directional pull yielded a higher ($\mu = 77.8\%$, $\sigma = 32.8\%$) interpretation accuracy than Directional interrupt ($\mu = 62.5\%$, $\sigma = 33.4\%$), with a chance level of 50%. However, the analysis did not reveal a significant difference ($V = 21.5, p > .05$).

Interpretation confidence. Participants also self-reported their confidence in interpreting the conveyed direction correctly. In line with the interpretation accuracies, participants had higher confidence when interpreting the direction conveyed by Directional pull compared to Directional interrupt ($\tilde{x} = 6$ vs. $\tilde{x} = 5$; both MAD = 1.5). We did not find a significant ($V = 28, p > .05$) effect.

User preferences. Ten participants indicated a clear preference for Directional pull over Directional interrupt for conveying the direction of an imminent body actuation.

Subjective feedback. P1 interpreted the Directional interrupt cue positively as *"showing a little bit of the motion already... the motion in very small."* However, five participants pointed to problems when interpreting the cue as the system moves the arm forth into the intended direction and then again back because they then *"have to figure out which one was the first [direction] that's relevant"* (P9). While the cue is still easy to detect, this additional step makes interpreting the conveyed direction more challenging, which is reflected by its low interpretation accuracies.

Feedback on Directional pull was mainly positive: Participants compared it to a physical guidance (n=6) with *"a natural affordance on where I should be moving"* (P8); P7 added: *"it's this whole embodied idea, where I don't need to think."* These experiences might explain both the higher interpretation accuracies and the clear preference for this cue.

5.3 Task 3: Understanding the Target of an Imminent Motion

Task 3 compared two levels of Motion Target Cue (Targeted interrupt, Targeted pull) for conveying the target of an imminent motion intent. Figure 9 provides an overview of the results.

Detection accuracy. The results show that Targeted pull yielded a high detection accuracy of $\mu = 86.1\%$, $\sigma = 22.3\%$. All instances of Targeted interrupt have been detected ($\mu = 100.0\%$, $\sigma = 0\%$). We did not find a significant effect of Motion Target Cue ($V = 1$, $p > .05$) on the detection accuracy.

Detection confidence. Participants reported a very high detection confidence of $\tilde{x} = 7$ (MAD = 0) for both cues. We did not find a significant ($V = 1, p > .05$) difference, indicating that both cues are clearly noticeable.

Response time. We found significantly ($t(11) = 4.02, p < .005$) faster response times for Targeted interrupt ($\mu = 2.3s$, $\sigma =$

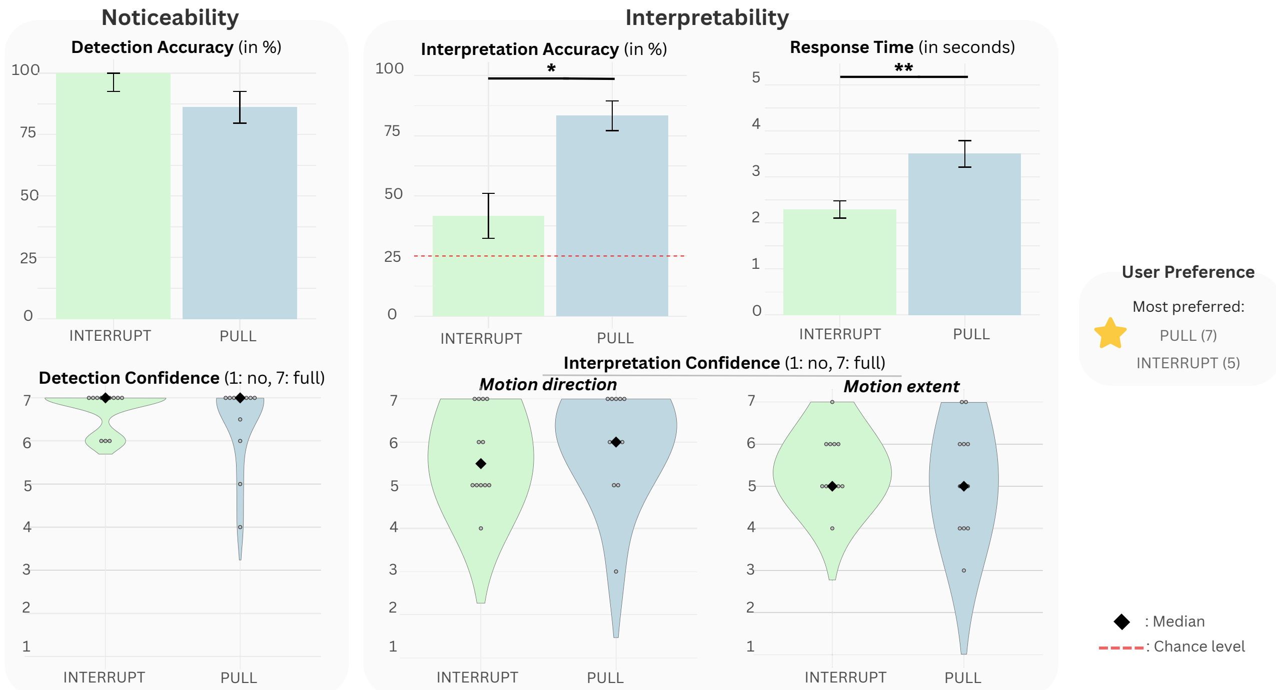

Figure 9: Results of Task 3 show that both proprioceptive cues could be correctly and confidently detected. Targeted pull yielded a higher interpretation accuracy, but slower response times compared to Targeted interrupt. The confidence in interpreting motion direction and extent are comparable. Users indicated a slight preference for Targeted pull. All error bars depict the standard error.

1.1s) compared to Targeted pull ($\mu = 3.5s$, $\sigma = 1.6s$) with a large ($d = 1.16$) effect size.

Interpretation accuracy. To interpret the target intent, participants had to correctly state both, the perceived direction (*flexion* or *extension*) and extent of the upcoming motion (*small* or *large*), yielding a chance level of 25%. The analysis revealed significantly ($V = 44, p < .05$) higher target interpretation accuracies for Targeted pull ($\mu = 83.3\%$, $\sigma = 21.3\%$) compared to Targeted interrupt ($\mu = 41.7\%$, $\sigma = 32.2\%$) with a large ($r = 0.96$) effect size. As the target intent includes both direction and motion extent, we further analyzed the interpretation accuracy for each property separately to examine whether the effectiveness of the cues varied depending on the type of information conveyed. We found significantly higher interpretation accuracies of the motion direction for Targeted pull ($\mu = 100.0\%$, $\sigma = 0\%$) compared to Targeted interrupt ($\mu = 69.4\%$, $\sigma = 22.3\%$, V = 45, p < .01) with a large ($r = 1$) effect size. Contrary, we did not find a significant effect of the Motion Target Cue on the interpretation accuracy of the motion extent (Targeted pull: $\mu = 83.3\%$, $\sigma = 21.3\%$; Targeted interrupt: $\mu = 61.1\%$, $\sigma = 31.2\%$, $V = 35.5, p > .05$).

Interpretation confidences. Participants stated confidences for having correctly interpreted the direction of the imminent motion in median of $\tilde{x} = 6$ for Targeted pull and $\tilde{x} = 5$ for Targeted interrupt (both MAD = 1.5). They stated slightly lower confidences in interpreting the motion extent with a median of $\tilde{x} = 5$ (MAD = 1.5) for both cues, consistent with the lower interpretation accuracies of the motion extent. The tests did not reveal a significant effect for the interpretation confidence of the direction ($V = 25, p > .05$) and the extent ($V = 10.5, p > .05$), respectively.

User preferences. Participants indicated a slight preference for Targeted pull for conveying target intent. This proprioceptive cue was ranked first by seven participants, while five participants preferred Targeted interrupt.

Subjective feedback. For Targeted interrupt, two angular displacements encoded the extent of the upcoming motion. The large displacement felt distracting for half of the participants (n=6) as it *"feels like it forced me against my motion"* (P11). This results in a less seamless integration, but clearer detectability and faster reactions.

Compared to Targeted interrupt, Targeted pull was more effective in conveying intent. Yet, participants noted that the torque required to convey a large motion extent might interfere with their primary activity (n=6): *"this is the best for me to understand the [intent]. But is it the best for the performance? I think no"* (P4). In contrast, P12 felt that higher torques integrated particularly well as resisting forces naturally fit the physical workout task.

5.4 Comparison Across Intents

The three tasks shared the detection accuracy, confidence, and response time as dependent variables. All cues across tasks achieved high detection accuracies and confidences. However, response times notably increased with the amount of information participants had to interpret, prompting a follow-up analysis comparing mean response times across tasks. Unsurprisingly, solely understanding the onset of an imminent motion generally was the fastest ($\mu = 1.1s, \sigma = 0.6s$), as it does not require any further interpretation, followed by interpreting direction ($\mu = 1.9s$, $\sigma = 1.1s$) and target ($\mu = 2.9s, \sigma = 1.4s$). A Friedman test revealed a significant ($\chi^2(2) = 18.5, p < .001$) effect with a large ($W = 0.8$) effect size. Post-hoc pairwise Wilcoxon signed-rank tests confirmed significantly faster times for interpreting the motion onset compared to both direction ($V = 77$, $p < .0001$) and target ($V = 0, p < .0001$) as well as significantly ($V = 3, p < .005$) faster response times for direction compared to target, indicating an increase in cognitive load when more complex information are conveyed.

5.5 User Perspectives on the Proprioceptive Cues

We conducted a thematic analysis to better understand participants' experiences with the proprioceptive cues, providing further insights into their qualities and relevant design considerations. We structure the results around two themes:

Proprioceptive cues enhanced the expressiveness of the conveyed intent beyond mere information delivery. The results of our analysis suggest that the proprioceptive cues conveyed not only the actual intent, but also impacted its perceived urgency and added an additional affective layer of interpretation:

Several participants noted that the proprioceptive cues elicit different tones of interactions which shape the perceived urgency of the imminent motion. The descriptions of these tones ranged from a gentle suggestion, guidance, and advice to a rather strict instruction, notification, command, or alert. DIRECTIONAL and TARGETED PULL were often described as guidance or suggestion because *"it's also showing how to do it instead of just a symbolic meaning"* (P8). According to P5, a suggestion in this context implies that the user has the option to decline. Conversely, more forceful or disruptive cues such as INTERRUPT would rather resemble commands which the user must obey (P8).

Participants also often attributed human-like qualities to the interaction, adding an affective layer to their interpretation of intent. This tendency was implicitly reflected in their choice of words, but also explicitly stated when they mentioned they *"definitely gave the exoskeleton a character"* (P5). This character was shaped by the proprioceptive cues: When moving forcefully, some participants described it as grumpy (P5), aggressive (P3, P12), or angry (P9). These forceful cues in turn sometimes also evoked emotions: While some participants emphasized that these motions could scare (P2, P3) the user, others found them rather motivating (P11). Adding to this, many participants also drew on analogies from interpersonal interaction to describe their experiences. In particular participants frequently described PULL as a human-like motion (P3, P5, P9) that resembles situations in which the user receives friendly support, for instance, *"if [your partner] wants to guide your body towards something or wants to keep you away from something"* (P4) or when *"some coach is teaching me how to move my body"* (P7). INTERRUPT, in contrast, was generally compared to less gentle experiences with other human-beings, as *"if someone is shaking"* (P5) the arm to draw attention.

Proprioceptive cues should be adapted to the user's context and preferences. The analysis of the interviews reveals users' aspirations for a system that adapts torques, the selection of cues, and the motion property to be conveyed to user context and preference:

Participants noted that the torques should be adapted to the urgency of the motion intent: *"If it's like an important thing the robot wants to tell you because of safety reasons for example [...] it's probably better to have strong feedback"* (P2) whereas *"if the machine wants to just notify or teach some motion, so it's better to use a normal force"* (P9) as forceful motions feel *"quite like an emergency"* (P3). Furthermore, the urgency may also be a factor in the selection of the proprioceptive cue: *"[INTERRUPT] wakes you up, it just draws your attention to the exoskeleton"* (P4), *"[RESIST] might make me pay more attention"* (P5), but *"I wouldn't notice [BOOST] if I was really busy doing something"* (P5).

In addition, interpreting the intended target caused high cognitive load: *"I felt there was a point until which the most [cues] were actually helpful [...]. But [...] there was a clear saturation for me after which I felt like 'okay this is too much information'"* (P7). Consequently, participants reported on mitigation strategies (P3, P10, P11), such as shifting their focus more towards the system and their own body even before the cue occurred to be *"more active or reactive"* (P11).

Participants also wished to tailor the proprioceptive cues to their own desires. This involves personalizing physical parameters, such as force or speed due to varying subjective preferences and designing *"custom modes"* (P12). These should help to find the cues' *"sweet spot between just poking and distracting you. And just gentle enough but not ignorable"* (P4), while also avoiding incorrect interpretations that could cause expectation mismatches and frustration (P7).

6 Discussion & Implications

We now discuss the findings of the study and derive implications for the design of interpretable proprioceptive cues.

6.1 A Design Trade-off Between Response Time and Interpretation Accuracy

Our results highlight a central design trade-off between how quickly and how accurately the meaning of a cue can be interpreted (see Table 2). *Interrupt* produced the fastest responses, likely because it disrupted ongoing motion and thus stood out strongly. Yet this disruption also reduced interpretation accuracy when users had to identify spatial details like direction or extent. In contrast, cues that augmented user motion through assistive or resistive forces were slower to interpret but yielded higher accuracy, as they supported a more embodied and deliberate exploration of intent. Furthermore, participants generally preferred these cues due to their rather seamless integration into user's motion.

For solely conveying the onset of an imminent motion, all cues achieved high detection accuracies (>90%), indicating that both disruptive and motion-congruent cues can serve as reliable alerts during ongoing movement. However, once the conveyed intent became more complex, performance diverged. *Pull*-based cues maintained reasonably high interpretation accuracies (>75%), whereas

Property	**Interrupting**			**Augmenting**		
	Interrupt	*Directional Interrupt*	*Targeted Interrupt*	*Boost & Resist*	*Directional Pull*	*Targeted Pull*
Detection accuracy	✓ Higher (97-100%)			✓ High (86-100%)		
Response time	✓ Faster (0.8-2.5 s)			✗ Slower (1.2-3.3 s)		
Interpret. accuracy	/	✗ Lower (42-63%)		/	✓ Higher (78-83%)	
Rated as most preferred by *x%* of participants	25%	16.7%	41.7%	33.3% & 25%	83.3%	58.3%
Suited for ...	attention grabbing			communicating detailed information		

Table 2: A summary of the design trade-off between cues interrupting and augmenting user motion.

the interpretation accuracies of the *interrupt*-based cues decreased. A certain decrease could be expected for the *interrupts* conveying spatial information as the threshold for detecting an externally induced movement is lower than that for detecting its direction [29]. But while the interpretation accuracies of *interrupt* were still above chance, their performance is clearly below optimal.

Taken together, these findings suggest a layered design approach: *interrupts* can act as high-salience attention grabbers, while motion-congruent cues are better suited for communicating detailed spatial information. To mitigate interpretation errors and expectation mismatches, we recommend combining such proprioceptive cues with complementary modalities, where they could reinforce the presented information, enabling both rapid detection and robust interpretation.

6.2 Interpretable Proprioceptive Cues Should be Adaptive and Personalized

The results demonstrate the need for adaptive and personalized proprioceptive cues. First, interpretation times rise with the amount of conveyed information, yet users often have limited time and cognitive resources, making complex intents impractical. Considering the physical suitability is equally critical: Particularly interruptive and forceful cues disrupt ongoing movements, posing risks for user activities requiring high dexterity or involving fragile or hazardous objects. Cue parameters must also adapt to the user motion, as perceptual thresholds are affected by the dynamics of the ongoing motion [29, 40], and carefully balance noticeability, interpretability, and integration with ongoing movement. To achieve this in real-world systems, information levels and parameters should be automatically adjusted to match user activity, with optimization- and AI-based methods offering promising directions. Finally, such systems should support personalization, starting with custom modes and enabling users to teach the system when to favor specific cues.

6.3 The Affective Dimension of Body-Actuating Systems Should Be Considered

Body-actuating systems foster an intimate relationship with the user due to their close-to-body attachment. This intimate relationship makes it essential to also consider interaction qualities beyond quantitative performance. In the study, participants attributed human-like qualities and emotional responses to the system. These observations align with prior work arguing that haptic cues can convey and evoke emotions [2, 14], indicating a collaborative dimension even when the system merely signals an intended actuation. As in human interaction, where more urgent information are conveyed with greater emphasis, participants interpreted motion-congruent cues more like gentle guidance and disruptive cues as commands, influencing perceived urgency. This suggests that such cues could be strategically employed to convey the urgency of a motion intent, acknowledging that not all actuations are equally critical. Ultimately, while the attribution of human-like qualities may partly stem from unconscious sensemaking strategies [89], they can also foster trust and ease interaction [19, 93], warranting deeper exploration in future work.

6.4 Contextualizing with Other Studies

Localized proprioceptive cues enable the most direct way to deliver information compared to feedback relocated to other body parts. But delivered at the position where the motor action takes place, these cues may experience sensory attenuation when the joint moves. However, relocation is not a guaranteed solution, as other body parts may also move or be actuated themselves, while alternative modalities may be susceptible to sensory attenuation, too. Alternative modalities, nonetheless, offer distinct advantages. To better situate the performance of the proprioceptive cues, we compare our findings with prior work across modalities:

Conveying the onset of an imminent motion. We reviewed prior HCI work reporting detection accuracy and response time of wearable notifications under dynamic conditions (e.g., walking or running), which better match our study than static contexts. In our study, all three proprioceptive cues conveying the motion onset achieved fast response times (0.8–1.3 s) and high detection accuracies (91.7-100%). By comparison, on-body visual feedback showed wide variability, with response times from 2.9 to 76 seconds [49, 67] and detection accuracies of 89.6–95.2% [67], suggesting visual cues may be less suited for fast communication in dynamic contexts. In contrast, audio feedback was fast (1.6-1.9 s) and achieved high accuracies (>99.2%) [67], indicating a strong potential for mobile contexts. Yet, it may be less effective in noisy environments. For haptic modalities, vibrotactile feedback yielded response times between 1.3 s [67] to above 2.5 s [38]; detection accuracies varied largely depending on the body part, ranging from 98.4% on the finger [67] to ~30% on the thigh [38]. Poking yielded similar times (1.6-2 s) and accuracies between 88.2–96.8% [4, 67]. Other modalities such as pinch, moisture, suck or brush were slower (2.1–2.5 s), but achieved comparable detection accuracies (84–95.3%) [4]. Finally, thermal feedback was substantially slower (3.0-14.9 s) [67, 90] with accuracies between 76%–92% [4, 67].

The proposed proprioceptive cues achieve comparatively faster response times and competitive detection accuracies while the user is moving. Yet, they do not require a complementary sensory channel, or additional haptic actuators, hence offering a particularly integrated way for body-actuating systems to conveying the onset of an imminent motion.

Conveying direction and target of an imminent motion. Directly comparing response times and accuracies for direction and target intent is challenging due to differing performance metrics (e.g., angular error vs. accuracy) and study conditions. While diverse haptic modalities were investigated to convey directionality (e.g., [36, 62, 75, 77]), vibration remains the dominant modality. A few studies offer sufficient overlap in granularity of directions and body location to allow for rough comparisons: For instance, binary directional cues via vibrotactile feedback on the hand achieved 75–97% accuracy with response times of 0.7–1.2 s [69], while similar cues on the forearm yielded 93% accuracy and 0.4–0.65 s response times [35]. In contrast, saltatory vibration mappings typically yielded slower response times (~2.3–4.5 s) [3, 48], but comparably high accuracies (e.g., [54]). The response times for interpreting directional cues in our study (1.6–2.3 s) fall between those of single and saltatory vibrotactile cues. Although our interpretation accuracies (62.5–77.8%) are lower, the study was conducted in a dynamic context unlike prior work [35, 54, 69], and vibrotactile detection is known to deteriorate during active motion [10, 64]. Integrating proprioceptive and vibrotactile feedback thus appears promising, combining the high detection accuracy of proprioceptive cues with the spatial clarity of vibrotactile signals for enhanced interpretation of more complex intents.

7 Limitations and Future Work

Our study has several limitations. We discuss them now and outline how these could be addressed in future work.

Generalizing to other systems, body parts and more degrees-of-freedom (DoF). This study focused on proprioceptive cues for 1 DoF hinge joints, implemented in an elbow exoskeleton. We chose the exoskeleton as it represents core actuation strategies applicable to other body-actuating systems. For example, both exoskeletons and EMS-based systems can enforce or augment motion [20], suggesting similar designs may apply. However, future work should explore how user perception changes with different systems. Another interesting question for follow-up work is how the proposed cues generalize to other body parts, different joint types with more DoFs and motions beyond flexion-extension. For instance, the cues could be implemented in leg-based systems where the device might twitch before it helps the user stand up, or gently amplify a step to signal a change in walking direction.

Conveying further properties of motion. We focused on three fundamental properties of motion. Future research should explore additional properties, such as the force or speed of the imminent actuation, enabling users to preview the type of assistance and increasing the granularity of direction and motion extent. Moreover, different physical parameters such as the cue's speed could be explored to encode these properties. Second, the proposed approach conveys information about the motion *before* the action is initiated. Future work could examine conveying intent *during* the ongoing action. Here, inspiration could be taken from prior work, such as easing-in and out of the motion [78] or exaggerating the trajectory towards the target (e.g., [5]).

Comparison to other feedback modalities. While we contextualized our findings with prior work, future research should directly compare proprioceptive feedback to other modalities. However, how best to convey imminent motion through these modalities remains an open question. Furthermore, we designed the proprioceptive cues as brief signals preceding system takeover. Therefore, they should be distinguishable from the system's main actions. Yet, confusion may occur in certain circumstances. Here, multi-modal cues could help disambiguate and reduce sensory attenuation, to which localized proprioceptive feedback may be susceptible. Future work should also explore other haptic feedback as an alternative for tasks where proprioceptive cues interrupt performance.

Evaluating proprioceptive cues across broader samples and contexts. Our study provides first insights into the potential of proprioceptive feedback to convey motion intent. Although the sample size aligns with prior CHI work [4, 45, 66, 92], future work should involve larger sample sizes and more diverse user demographics. In the study task, the user and the system shared the same goal of a workout, with clearly assigned roles, a low cognitive and steady physical effort. Future work should assess the impact of interpretable cues on agency and safety and across diverse activities in in-the-wild scenarios, diverging user and system intentions, and varying cognitive and physical demands. Additionally, it will be also important to investigate how intent communication influences task performance.

8 Conclusion

In mixed-initiative settings, body-actuating systems may take control proactively. To mitigate unexpected body actuation, systems should communicate their motion intent before the action takes place. We propose proprioceptive feedback to deliver this information directly to the affected body part. We focus on three key properties of imminent motions: (1) either informing the user that a body actuation is imminent or (2) also about the direction or (3) target. For each property, we designed proprioceptive cues targeted at one degree-of-freedom joints and implemented them in an elbow exoskeleton. In a user study, we compared response times, interpretation accuracy and confidence. The results reveal that all cues are highly noticeable. However, their effectiveness in conveying information differed: Interruptive strategies appear beneficial when rapid interpretation is critical. Contrarily, if interpretation accuracy is prioritized, cues that augment the user's motion are recommended, despite slower response times. We further suggest combining such cues with other modalities to reinforce information and discuss the need for adaptability in embodied intent communication. We hope these findings serve as a valuable foundation for future research and contribute to the development of autonomous body-actuating systems that collaborate smoothly with humans.

Acknowledgments

We thank all participants of our user studies and Jule Enninghorst for her help in building the prototype. We also thank the reviewers for their insightful comments that helped to improve the paper.

References

[1] Nanao Akimichi, Kiyoshi Eguchi, and Kenji Suzuki. 2013. Myoelectric Controlled Prosthetic Hand with Continuous Force-Feedback Mechanism. In *2013 IEEE International Conference on Systems, Man, and Cybernetics*. 3354–3359. https://doi.org/10.1109/SMC.2013.572

[2] Jeremy N. Bailenson, Nick Yee, Scott Brave, Dan Merget, and David Koslow. 2007. Virtual Interpersonal Touch: Expressing and Recognizing Emotions Through Haptic Devices. *Human–Computer Interaction* 22, 3 (2007), 325–353. https://doi.org/10.1080/07370020701493509

[3] Karlin Bark, Emily Hyman, Frank Tan, Elizabeth Cha, Steven A Jax, Laurel J Buxbaum, and Katherine J Kuchenbecker. 2014. Effects of Vibrotactile Feedback on Human Learning of Arm Motions. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 23, 1 (2014), 51–63.

[4] Arpit Bhatia, Dhruv Kundu, Suyash Agarwal, Varnika Kairon, and Aman Parnami. 2021. Soma-noti: Delivering Notifications Through Under-clothing Wearables. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 221, 8 pages. https://doi.org/10.1145/3411764.3445123

[5] Christopher Bodden, Daniel Rakita, Bilge Mutlu, and Michael Gleicher. 2018. A Flexible Optimization-based Method for Synthesizing Intent-expressive Robot Arm Motion. *The International Journal of Robotics Research* 37, 11 (2018), 1376–1394.

[6] Robert Bogue. 2018. Exoskeletons–a review of industrial applications. *Industrial Robot: An International Journal* 45, 5 (2018), 585–590.

[7] Virginia Braun and Victoria Clarke. 2006. Using Thematic Analysis in Psychology. *Qualitative Research in Psychology* 3, 2 (2006), 77–101. https://doi.org/10.1191/1478088706qp063oa

[8] Adrian-Vasile Catană and Radu-Daniel Vatavu. 2023. Fingerhints: Understanding Users' Perceptions of and Preferences for On-Finger Kinesthetic Notifications. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 518, 17 pages. https://doi.org/10.1145/3544548.3581022

[9] Tathagata Chakraborti, Anagha Kulkarni, Sarath Sreedharan, David Smith, and Subbarao Kambhampati. 2018. Explicability? Legibility? Predictability? Transparency? Privacy? Security? The Emerging Landscape of Interpretable Agent Behavior. In *Proceedings of the Twenty-Ninth International Conference on Automated Planning and Scheduling (ICAPS '19)*. Association for the Advancement of Artificial Intelligence.

[10] C Elaine Chapman, MC Bushnell, D Miron, GH Duncan, and JP Lund. 1987. Sensory Perception During Movement in Man. *Experimental Brain Research* 68, 3 (1987), 516–524.

[11] Chia-Yu Chen, Yen-Yu Chen, Yi-Ju Chung, and Neng-Hao Yu. 2016. Motion Guidance Sleeve: Guiding the Forearm Rotation through External Artificial Muscles. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 3272–3276. https://doi.org/10.1145/2858036.2858275

[12] Jacob Cohen. 1988. *Statistical Power Analysis for the Behavioral Sciences*. Routledge. https://doi.org/10.4324/9780203771587

[13] John W Creswell. 2021. *A Concise Introduction to Mixed Methods Research*. SAGE publications.

[14] Tor-Salve Dalsgaard and Oliver Schneider. 2025. A Unified Model for Haptic Experience. *ACM Trans. Comput.-Hum. Interact.* 32, 1, Article 9 (April 2025), 38 pages. https://doi.org/10.1145/3711842

[15] Nathan DeVrio and Chris Harrison. 2025. Reel Feel: Rich Haptic XR Experiences Using an Active, Worn, Multi-String Device. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 610, 20 pages. https://doi.org/10.1145/3706598.3713615

[16] Anca Dragan and Siddhartha Srinivasa. 2013. Generating Legible Motion. In *Proceedings of Robotics: Science and Systems (RSS '14)*. 1–8.

[17] Anca D. Dragan, Shira Bauman, Jodi Forlizzi, and Siddhartha S. Srinivasa. 2015. Effects of Robot Motion on Human-Robot Collaboration. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction* (Portland, Oregon, USA) *(HRI '15)*. Association for Computing Machinery, New York, NY, USA, 51–58. https://doi.org/10.1145/2696454.2696473

[18] Anca D. Dragan, Kenton C.T. Lee, and Siddhartha S. Srinivasa. 2013. Legibility and Predictability of Robot Motion. In *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI '13)*. 301–308. https://doi.org/10.1109/HRI.2013.6483603

[19] Brian R. Duffy. 2003. Anthropomorphism and the Social Robot. *Robotics and Autonomous Systems* 42, 3 (2003), 177–190. https://doi.org/10.1016/S0921-8890(02)00374-3 Socially Interactive Robots.

[20] Sarah Faltaous, Marion Koelle, and Stefan Schneegass. 2022. From Perception to Action: A Review and Taxonomy on Electrical Muscle Stimulation in HCI. In *Proceedings of the 21st International Conference on Mobile and Ubiquitous Multimedia* (Lisbon, Portugal) *(MUM '22)*. Association for Computing Machinery, New York, NY, USA, 159–171. https://doi.org/10.1145/3568444.3568460

[21] Sarah Faltaous, Chris Schönherr, Henrik Detjen, and Stefan Schneegass. 2019. Exploring Proprioceptive Take-over Requests for Highly Automated Vehicles. In *Proceedings of the 18th International Conference on Mobile and Ubiquitous Multimedia* (Pisa, Italy) *(MUM '19)*. Association for Computing Machinery, New York, NY, USA, Article 13, 6 pages. https://doi.org/10.1145/3365610.3365644

[22] Wu Fan, Zhe Dai, Bin Zhang, Long He, Min Pan, Jingang Yi, and Tao Liu. 2024. HyExo: A Novel Quasi-passive Hydraulic Exoskeleton for Load-carrying Augmentation. *IEEE/ASME Transactions on Mechatronics* 30, 1 (2024), 144–155.

[23] Cathy Fang, Yang Zhang, Matthew Dworman, and Chris Harrison. 2020. Wireality: Enabling Complex Tangible Geometries in Virtual Reality with Worn Multi-String Haptics. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3313831.3376470

[24] Stefan Fornalski, Ranjan Gupta, and Thay Q Lee. 2003. Anatomy and Biomechanics of the Elbow Joint. *Sports Medicine and Arthroscopy Review* 11, 1 (2003), 1–9.

[25] Uwe Gruenefeld, Lars Prädel, Jannike Illing, Tim Stratmann, Sandra Drolshagen, and Max Pfingsthorn. 2020. Mind the ARm: Realtime Visualization of Robot Motion Intent in Head-Mounted Augmented Reality. In *Proceedings of Mensch Und Computer 2020* (Magdeburg, Germany) *(MuC '20)*. Association for Computing Machinery, New York, NY, USA, 259–266. https://doi.org/10.1145/3404983.3405509

[26] Xiaochi Gu, Yifei Zhang, Weize Sun, Yuanzhe Bian, Dao Zhou, and Per Ola Kristensson. 2016. Dexmo: An Inexpensive and Lightweight Mechanical Exoskeleton for Motion Capture and Force Feedback in VR. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 1991–1995. https://doi.org/10.1145/2858036.2858487

[27] Sebastian Günther, Mohit Makhija, Florian Müller, Dominik Schön, Max Mühlhäuser, and Markus Funk. 2019. PneumAct: Pneumatic Kinesthetic Actuation of Body Joints in Virtual Reality Environments. In *Proceedings of the 2019 on Designing Interactive Systems Conference* (San Diego, CA, USA) *(DIS '19)*. Association for Computing Machinery, New York, NY, USA, 227–240. https://doi.org/10.1145/3322276.3322302

[28] Sebastian Günther, Florian Müller, Markus Funk, Jan Kirchner, Niloofar Dezfuli, and Max Mühlhäuser. 2018. TactileGlove: Assistive Spatial Guidance in 3D Space through Vibrotactile Navigation. In *Proceedings of the 11th PErvasive Technologies Related to Assistive Environments Conference* (Corfu, Greece) *(PETRA '18)*. Association for Computing Machinery, New York, NY, USA, 273–280. https://doi.org/10.1145/3197768.3197785

[29] Lesley A Hall and DI McCloskey. 1983. Detections of Movements Imposed on Finger, Elbow and Shoulder Joints. *The Journal of Physiology* 335, 1 (1983), 519–533.

[30] Mahmoud Hassan, Florian Daiber, Frederik Wiehr, Felix Kosmalla, and Antonio Krüger. 2017. FootStriker: An EMS-based Foot Strike Assistant for Running. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 1, Article 2 (mar 2017), 18 pages. https://doi.org/10.1145/3053332

[31] Seongkook Heo, Christina Chung, Geehyuk Lee, and Daniel Wigdor. 2018. Thor's Hammer: An Ungrounded Force Feedback Device Utilizing Propeller-Induced Propulsive Force. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3173574.3174099

[32] Yun Ho, Romain Nith, Peili Jiang, Shan-Yuan Teng, and Pedro Lopes. 2025. Generative Muscle Stimulation: Physical Assistance by Constraining Multimodal-AI with Biomechanical Knowledge. *arXiv preprint arXiv:2505.10648* (2025).

[33] Eric Horvitz. 1999. Uncertainty, Action, and Interaction: In Pursuit of Mixed-Initiative Computing. *IEEE Intelligent Systems* 14, 5 (1999), 17–20.

[34] Felix Huppert, Gerold Hoelzl, and Matthias Kranz. 2021. GuideCopter - A Precise Drone-Based Haptic Guidance Interface for Blind or Visually Impaired People. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 218, 14 pages. https://doi.org/10.1145/3411764.3445676

[35] Chris Jansen, Arjen Oving, Hendrik-Jan van Veen, et al. 2004. Vibrotactile Movement Initiation. In *Proceedings of Eurohaptics*. Citeseer, 110–117.

[36] Seungwoo Je, Minkyeong Lee, Yoonji Kim, Liwei Chan, Xing-Dong Yang, and Andrea Bianchi. 2018. PokeRing: Notifications by Poking Around the Finger. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3173574.3174116

[37] Merel M. Jung and Geke D. S. Ludden. 2018. Potential of Exoskeleton Technology to Assist Older Adults with Daily Living. In *Extended Abstracts of the 2018 CHI*

Conference on Human Factors in Computing Systems (Montreal QC, Canada) *(CHI EA '18)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3170427.3188464
[38] Idin Karuei, Karon E. MacLean, Zoltan Foley-Fisher, Russell MacKenzie, Sebastian Koch, and Mohamed El-Zohairy. 2011. Detecting Vibrations Across the Body in Mobile Contexts. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 3267–3276. https://doi.org/10.1145/1978942.1979426
[39] Shunichi Kasahara, Jun Nishida, and Pedro Lopes. 2019. Preemptive Action: Accelerating Human Reaction Using Electrical Muscle Stimulation Without Compromising Agency. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. 1–15.
[40] Hubert Kim and Alan T Asbeck. 2021. Just Noticeable Differences for Elbow Joint Torque Feedback. *Scientific Reports* 11, 1 (2021), 23553.
[41] Lawrence H. Kim and Sean Follmer. 2021. Generating Legible and Glanceable Swarm Robot Motion through Trajectory, Collective Behavior, and Pre-Attentive Processing Features. *Journal of Human-Robot Interaction* 10, 3, Article 21 (2021), 25 pages. https://doi.org/10.1145/3442681
[42] Jacqlyn King, Elizabeth Harding, and Andrew Karduna. 2013. The Shoulder and Elbow Joints and Right and Left Sides Demonstrate Similar Joint Position Sense. *Journal of motor behavior* 45, 6 (2013), 479–486.
[43] Matti Krüger, Christiane B Wiebel-Herboth, and Heiko Wersing. 2021. Tactile Encoding of Directions and Temporal Distances to Safety Hazards Supports Drivers in Overtaking and Intersection Scenarios. *Transportation Research Part F: Traffic Psychology and Behaviour* 81 (2021), 201–222.
[44] Gregory Lemasurier, Gal Bejerano, Victoria Albanese, Jenna Parrillo, Holly A. Yanco, Nicholas Amerson, Rebecca Hetrick, and Elizabeth Phillips. 2021. Methods for Expressing Robot Intent for Human–Robot Collaboration in Shared Workspaces. *J. Hum.-Robot Interact.* 10, 4, Article 40 (sep 2021), 27 pages. https://doi.org/10.1145/3472223
[45] Zhen Li, Joannes Chan, Joshua Walton, Hrvoje Benko, Daniel Wigdor, and Michael Glueck. 2021. Armstrong: An Empirical Examination of Pointing at Non-Dominant Arm-Anchored UIs in Virtual Reality. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 123, 14 pages. https://doi.org/10.1145/3411764.3445064
[46] Weimin Liu, Qingkun Li, Zhenyuan Wang, Wenjun Wang, Chao Zeng, and Bo Cheng. 2023. A Literature Review on Additional Semantic Information Conveyed from Driving Automation Systems to Drivers Through Advanced In-vehicle HMI Just Before, During, and Right After Takeover Request. *International Journal of Human–Computer Interaction* 39, 10 (2023), 1995–2015.
[47] Pedro Lopes, Alexandra Ion, Willi Mueller, Daniel Hoffmann, Patrik Jonell, and Patrick Baudisch. 2015. Proprioceptive Interaction. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 939–948. https://doi.org/10.1145/2702123.2702461
[48] Jose V Salazar Luces, Keisuke Okabe, Yoshiki Murao, and Yasuhisa Hirata. 2017. A Phantom-sensation Based Paradigm for Continuous Vibrotactile Wrist Guidance in Two-dimensional Space. *IEEE Robotics and Automation Letters* 3, 1 (2017), 163–170.
[49] Kent Lyons. 2016. Visual parameters impacting reaction times on smartwatches. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Florence, Italy) *(MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 190–194. https://doi.org/10.1145/2935334.2935344
[50] Stefano Massardi, David Pinto-Fernandez, Jan Babič, Miha Dežman, Andrej Trošt, Victor Grosu, Dirk Lefeber, Carlos Rodriguez, Jule Bessler, Leendert Schaake, et al. 2023. Relevance of Hazards in Exoskeleton Applications: A Survey-based Enquiry. *Journal of Neuroengineering and Rehabilitation* 20, 1 (2023), 68.
[51] Takafumi Matsumaru, Takashi Kusada, and Kazuya Iwase. 2006. Mobile Robot with Preliminary-Announcement Function of Forthcoming Motion using Light-ray. In *2006 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '06)*. 1516–1523. https://doi.org/10.1109/IROS.2006.281981
[52] Alyxander David May, Christian Dondrup, and Marc Hanheide. 2015. Show Me Your Moves! Conveying Navigation Intention of a Mobile Robot to Humans. In *2015 European Conference on Mobile Robots (ECMR) (ECMR '15)*. 1–6. https://doi.org/10.1109/ECMR.2015.7324049
[53] Philipp Mayring. 2000. Qualitative Content Analysis. *Forum Qualitative Sozialforschung / Forum: Qualitative Social Research* 1, 3 (2000). http://nbn-resolving.de/urn:nbn:de:0114-fqs0002204
[54] Troy McDaniel, Morris Goldberg, Daniel Villanueva, Lakshmie Narayan Viswanathan, and Sethuraman Panchanathan. 2011. Motor Learning Using a Kinematic-vibrotactile Mapping Targeting Fundamental Movements. In *Proceedings of the 19th ACM International Conference on Multimedia* (Scottsdale, Arizona, USA) *(MM '11)*. Association for Computing Machinery, New York, NY, USA, 543–552. https://doi.org/10.1145/2072298.2072369
[55] Marie Muehlhaus, Alexander Liggesmeyer, and Jürgen Steimle. 2025. ExoKit: A Toolkit for Rapid Prototyping of Interactions for Arm-based Exoskeletons. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 282, 17 pages. https://doi.org/10.1145/3706598.3713815
[56] Andreea Muresan, Jess Mcintosh, and Kasper Hornbæk. 2023. Using Feedforward to Reveal Interaction Possibilities in Virtual Reality. *ACM Trans. Comput.-Hum. Interact.* 30, 6, Article 82 (Sept. 2023), 47 pages. https://doi.org/10.1145/3603623
[57] Ali Nasr, Keaton Inkol, and John McPhee. 2025. Safety in Wearable Robotic Exoskeletons: Design, Control, and Testing Guidelines. *Journal of Mechanisms and Robotics* 17, 5 (2025), 050801.
[58] Arinobu Niijima and Shoichiro Takeda. 2025. Improving Putting Accuracy with Electrical Muscle Stimulation Feedback Guided by Muscle Synergy Analysis. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 362, 11 pages. https://doi.org/10.1145/3706598.3713605
[59] Romain Nith, Yun Ho, and Pedro Lopes. 2024. Splitbody: Reducing Mental Workload While Multitasking via Muscle Stimulation. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–11.
[60] Bastian Orthmann, Iolanda Leite, Roberto Bresin, and Ilaria Torre. 2023. Sounding Robots: Design and Evaluation of Auditory Displays for Unintentional Human-Robot Interaction. *Journal of Human-Robot Interaction* (aug 2023). https://doi.org/10.1145/3611655
[61] Max Pascher, Uwe Gruenefeld, Stefan Schneegass, and Jens Gerken. 2023. How to Communicate Robot Motion Intent: A Scoping Review. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 409, 17 pages. https://doi.org/10.1145/3544548.3580857
[62] Roshan Lalitha Peiris, Yuan-Ling Feng, Liwei Chan, and Kouta Minamizawa. 2019. ThermalBracelet: Exploring Thermal Haptic Feedback Around the Wrist. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–11. https://doi.org/10.1145/3290605.3300400
[63] Max Pfeiffer, Tim Dünte, Stefan Schneegass, Florian Alt, and Michael Rohs. 2015. Cruise Control for Pedestrians: Controlling Walking Direction using Electrical Muscle Stimulation. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 2505–2514. https://doi.org/10.1145/2702123.2702190
[64] LJ Post, IC Zompa, and CE Chapman. 1994. Perception of Vibrotactile Stimuli During Motor Activity in Human Subjects. *Experimental Brain Research* 100, 1 (1994), 107–120.
[65] Tommaso Proietti, Vincent Crocher, Agnes Roby-Brami, and Nathanael Jarrasse. 2016. Upper-limb Robotic Exoskeletons for Neurorehabilitation: A Review on Control Strategies. *IEEE Reviews in Biomedical Engineering* 9 (2016), 4–14.
[66] Ashwin Ram and Shengdong Zhao. 2022. Does Dynamically Drawn Text Improve Learning? Investigating the Effect of Text Presentation Styles in Video Learning. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 89, 12 pages. https://doi.org/10.1145/3491102.3517499
[67] Thijs Roumen, Simon T. Perrault, and Shengdong Zhao. 2015. NotiRing: A Comparative Study of Notification Channels for Wearable Interactive Rings. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 2497–2500. https://doi.org/10.1145/2702123.2702350
[68] Makoto Sato. 2002. Development of String-based Force Display: SPIDAR. In *8th International Conference on Virtual Systems and Multimedia*. Citeseer, 1034–1039.
[69] Lorenzo Scalera, Stefano Seriani, Paolo Gallina, Massimiliano Di Luca, and Alessandro Gasparetto. 2018. Experimental Evaluation of Vibrotactile Training Mappings for Dual-joystick Directional Guidance. In *International Conference on Human Haptic Sensing and Touch Enabled Computer Applications*. Springer, 575–586.
[70] Daniel Schmicking and Shaun Gallagher. 2010 edition. *Handbook of Phenomenology and Cognitive Science*. Springer.
[71] Stefan Schneegass and Rufat Rzayev. 2016. Embodied Notifications: Implicit Notifications Through Electrical Muscle Stimulation. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (Florence, Italy) *(MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 954–959. https://doi.org/10.1145/2957265.2962663
[72] Vimal Darius Seetohul, Katrin Schweitzer, and Matthias Böhmer. 2023. Towards Improving Spatial Orientation using Electrical Muscle Stimulation as Tactile and Force Feedback. In *Proceedings of the 22nd International Conference on Mobile and Ubiquitous Multimedia* (Vienna, Austria) *(MUM '23)*. Association for Computing Machinery, New York, NY, USA, 512–514. https://doi.org/10.1145/3626705.3631792
[73] Daniel Spelmezan, Mareike Jacobs, Anke Hilgers, and Jan Borchers. 2009. Tactile Motion Instructions for Physical Activities. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Boston, MA, USA) *(CHI*

'09). Association for Computing Machinery, New York, NY, USA, 2243–2252. https://doi.org/10.1145/1518701.1519044

[74] Dennis Stanke, Tim Duente, Kerem Can Demir, and Michael Rohs. 2023. Can You Ear Me? A Comparison of Different Private and Public Notification Channels for the Earlobe. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 3, Article 123 (sep 2023), 23 pages. https://doi.org/10.1145/3610925

[75] Andrew A. Stanley and Katherine J. Kuchenbecker. 2012. Evaluation of Tactile Feedback Methods for Wrist Rotation Guidance. *IEEE Transactions on Haptics* 5, 3 (2012), 240–251. https://doi.org/10.1109/TOH.2012.33

[76] Benjamin Stephens-Fripp, Rahim Mutlu, and Gursel Alici. 2018. Applying Mechanical Pressure and Skin Stretch Simultaneously for Sensory Feedback in Prosthetic Hands. In *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*. 230–235. https://doi.org/10.1109/BIOROB.2018.8487689

[77] Evan Strasnick, Jessica R. Cauchard, and James A. Landay. 2017. BrushTouch: Exploring an Alternative Tactile Method for Wearable Haptics. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 3120–3125. https://doi.org/10.1145/3025453.3025759

[78] Daniel Szafir, Bilge Mutlu, and Terrence Fong. 2014. Communication of Intent in Assistive Free Flyers. In *Proceedings of the 2014 ACM/IEEE International Conference on Human-Robot Interaction* (Bielefeld, Germany) *(HRI '14)*. Association for Computing Machinery, New York, NY, USA, 358–365. https://doi.org/10.1145/2559636.2559672

[79] Daniel Szafir, Bilge Mutlu, and Terry Fong. 2015. Communicating Directionality in Flying Robots. In *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction (HRI '15)*. Association for Computing Machinery, New York, NY, USA, 19–26. https://doi.org/10.1145/2696454.2696475

[80] Yudai Tanaka, Jun Nishida, and Pedro Lopes. 2022. Electrical Head Actuation: Enabling Interactive Systems to Directly Manipulate Head Orientation. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 262, 15 pages. https://doi.org/10.1145/3491102.3501910

[81] Yudai Tanaka, Jacob Serfaty, and Pedro Lopes. 2024. Haptic Source-Effector: Full-Body Haptics via Non-Invasive Brain Stimulation. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 411, 15 pages. https://doi.org/10.1145/3613904.3642483

[82] Yudai Tanaka, Akifumi Takahashi, and Pedro Lopes. 2023. Interactive Benefits from Switching Electrical to Magnetic Muscle Stimulation. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology* (San Francisco, CA, USA) *(UIST '23)*. Association for Computing Machinery, New York, NY, USA, Article 69, 12 pages. https://doi.org/10.1145/3586183.3606812

[83] Shan-Yuan Teng, K. D. Wu, Jacqueline Chen, and Pedro Lopes. 2022. Prolonging VR Haptic Experiences by Harvesting Kinetic Energy from the User. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology* (Bend, OR, USA) *(UIST '22)*. Association for Computing Machinery, New York, NY, USA, Article 39, 18 pages. https://doi.org/10.1145/3526113.3545635

[84] Jo Vermeulen, Kris Luyten, Elise van den Hoven, and Karin Coninx. 2013. Crossing the bridge over Norman's Gulf of Execution: revealing feedforward's true identity. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 1931–1940. https://doi.org/10.1145/2470654.2466255

[85] Steeven Villa, Finn Jacob Eliyah Krammer, Yannick Weiss, Robin Welsch, and Thomas Kosch. 2025. Understanding the Influence of Electrical Muscle Stimulation on Motor Learning: Enhancing Motor Learning or Disrupting Natural Progression?. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 366, 17 pages. https://doi.org/10.1145/3706598.3714183

[86] David Wagmann, Marie Muehlhaus, and Jürgen Steimle. 2025. Move with Style! Enhancing Avatar Embodiment in Virtual Reality through Proprioceptive Motion Feedback. *Proceedings of the 38th Annual ACM Symposium on User Interface Software and Technology* (2025). https://doi.org/10.1145/3746059.3747649

[87] Dian Wang, Colin Kohler, Andreas ten Pas, Alexander Wilkinson, Maozhi Liu, Holly Yanco, and Robert Platt. 2022. Towards Assistive Robotic Pick and Place in Open World Environments. In *Robotics Research*, Tamim Asfour, Eiichi Yoshida, Jaeheung Park, Henrik Christensen, and Oussama Khatib (Eds.). Springer International Publishing, Cham, 360–375.

[88] David Warnock, Marilyn McGee-Lennon, and Stephen Brewster. 2011. The Role of Modality in Notification Performance. In *IFIP Conference on Human-Computer Interaction*. Springer, 572–588.

[89] J. N. Wilkenfeld, S. Kim, S. Upasani, G. L. Kirkwood, N. E. Dunbar, and D. Srinivasan. 2023. Sensemaking, Adaptation and Agency in Human-exoskeleton Synchrony. *Frontiers in Robotics and AI* 10 (2023), 14 pages. https://doi.org/10.3389/frobt.2023.1207052

[90] Graham Wilson, Martin Halvey, Stephen A. Brewster, and Stephen A. Hughes. 2011. Some Like It Hot: Thermal Feedback for Mobile Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 2555–2564. https://doi.org/10.1145/1978942.1979316

[91] Willa Yunqi Yang, Yifan Zou, Jingle Huang, Raouf Abujaber, and Ken Nakagaki. 2024. TorqueCapsules: Fully-Encapsulated Flywheel Actuation Modules for Designing and Prototyping Movement-Based and Kinesthetic Interaction. In *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology* (Pittsburgh, PA, USA) *(UIST '24)*. Association for Computing Machinery, New York, NY, USA, Article 98, 15 pages. https://doi.org/10.1145/3654777.3676364

[92] Hui-Shyong Yeo, Xiao-Shen Phang, Steven J. Castellucci, Per Ola Kristensson, and Aaron Quigley. 2017. Investigating Tilt-based Gesture Keyboard Entry for Single-Handed Text Entry on Large Devices. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 4194–4202. https://doi.org/10.1145/3025453.3025520

[93] Jakub Złotowski, Diane Proudfoot, Kumar Yogeeswaran, and Christoph Bartneck. 2015. Anthropomorphism: Opportunities and Challenges in Human-robot Interaction. *International Journal of Social Robotics* 7 (2015), 347–360.