

Intermanual Deictics: Uncovering Users' Gesture Preferences for Opposite-Arm Referential Input, from Fingers to Shoulder

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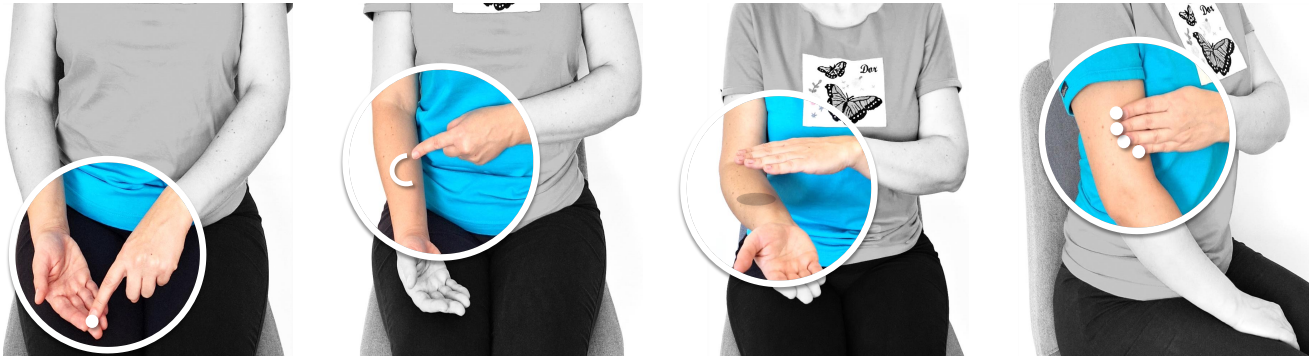


Figure 1: Intermanual deictics are referential gestures involving the opposite arm, which serves as both support and reference for input. Examples include tapping a specific finger (left), drawing a symbol on the forearm (middle-left), hovering the hand above the forearm (middle-right), or touching the upper arm with the hand forming a specific pose (right). In this work, we report on user preferences for intermanual deictics involving the opposite *palm*, *forearm*, and *upper arm*, such as the gestures illustrated in this figure, based on data from an extended end-user elicitation study on on-body input, involving 75 participants.

Abstract

We examine *intermanual deictics*, a distinctive class of gesture input characterized by an intermanual structure, asymmetric postural-manipulative articulation, and a deictic nature, drawing from both on-skin and bimanual mid-air gestures. To understand user preferences for gestures featuring these characteristics, we conducted a large-sample end-user elicitation study with 75 participants, who proposed intermanual deictics involving the opposite *palm*, *forearm*, and *upper arm*. Our results reveal a strong preference for physical-contact gestures primarily performed with the index finger, with strokes (62.4%) and touch input (28.8%) being most common, complemented by some preference for non-contact gestures (5.2%). We report similar agreement rates across gestures elicited in the three arm regions, averaging 26.3%, with higher agreement between the forearm and upper arm. We also present a consensus set of sixty gestures for effecting generic commands in interactive systems, along with design principles encompassing multiple practical implications for interactions that incorporate intermanual deictics.

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CCS Concepts

• Human-centered computing → Empirical studies in HCI; Gestural input; User studies.

Keywords

Gesture input, touch input, on-body interaction, body-referential input, intermanual gestures, gesture elicitation, gesture analysis, gesture set, bimanual gestures, design guidelines

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1 Introduction

On-body and body-referential input present many distinctive qualities in the landscape of gesture interaction techniques, including speed [59], always-availability [25], high expressiveness [47,70], uniform addressability [61], effectiveness in eyes-free input due to proprioception [14], and dual tactile feedback, both at the interaction location on the support body part and on the hand performing the gesture [20]. Moreover, specific body parts can be directly mapped to screen layouts on conventional digital devices, such as the palm [14,19,68] or forearm [6,48], and offer intuitive support for interactions in virtual reality environments [33]. Additionally, the spatial location of the body part receiving input can serve as an

extra modality [24,45], while anatomical landmarks on the body, such as finger joints and nails, as well as personal landmarks, such as scars and tattoos, can be leveraged to further enhance the input efficiency of on-body input [58] and increase recall rates for virtual content mapped to the body [5]. We refer to Bergström and Hornbæk [4] and Villarreal-Narvaez et al. [64] for comprehensive overviews of on-skin, on-body, and whole-body user interfaces.

In this growing landscape of appropriating the human body for mediating interactions with computer systems, the scientific community has primarily focused on enabling technology for recognizing on-body input and designing interaction techniques that utilize the body as an I/O surface. Notable examples of technology include depth-sensing systems [14,19,22,59], wrist-mounted sensing with cameras [69], proximity sensors [68], radiofrequency emitters [75], armbands with bio-acoustic [25] and photoelectric [42] sensing, and forearm displays [48], among others. However, users' preferences for on-body gesture input have been examined to a significantly lesser extent. The few studies [8,41,70] that reported on such preferences have concentrated on the particularities of gestures specific to skin-based input, e.g., pulling, pinching, or squeezing the skin [70], bimanual gestures involving the hands touching each other [41], and differences between on-skin and mid-air gestures [8,27]. Unfortunately, this context has led to uneven progress in on-body user interfaces. While technology for building interactive systems featuring on-body input has advanced significantly, our understanding of user preferences for intuitive gestures remains limited.

In this work, we address this imbalance by reporting empirical results from an extended, large-sample end-user gesture elicitation study involving the body as a reference surface for input. We specifically focus on gestures involving regions of the opposite arm, such as the *palm*, *forearm*, and *upper arm*, as prior work [23,52,67] has shown that input in these regions is consistently preferred and regarded as the most socially acceptable compared to other body parts. Moreover, we posit that these gestures form a distinctive class of gesture input, which we refer to as *intermanual deictics*, in which one arm serves as both the support and reference for the other arm, e.g., tapping on the ring finger, drawing a symbol on the forearm, hovering the hand above the opposite arm, or touching the upper arm with the hand forming a specific pose; see Figure 1 for illustrations. In this context, we make the following contributions:

- (1) We formalize *intermanual deictics* as a distinctive gesture class in the landscape of gesture-based interaction, and highlight their quality properties—asynchronicity, deictic nature, and support-implementer referential action—compared to on-skin and bimanual gestures.
- (2) We report empirical results from an end-user elicitation study with 75 participants, who proposed intermanual deictics involving the *palm*, *forearm*, and *upper arm*. Our findings reveal a strong preference for strokes (62.4%) and touch (28.8%) input, primarily performed using the index finger, some preference for non-contact gestures (5.2%), and similar agreement rates across the three arm regions and larger agreement of gesture characteristics between the *forearm* and *upper arm*. Based on these results, we compile a consensus set of sixty gestures involving the *palm*, *forearm*, and *upper arm* for effecting generic commands in interactive systems.
- (3) We use our findings to derive a set of eight design principles encompassing sixteen practical implications for intermanual deictics, where the *palm*, *forearm*, and *upper arm* serve as both support and reference for input. Lastly, we capitalize on our insights to propose directions for future work integrating intermanual deictics into on-body interaction.

2 Related Work

We relate to prior work on interactions performed on the body and skin [4,57], and provide an overview of findings from studies implementing end-user gesture elicitation [64,65,73], which is our method of choice for the scientific investigation in this work.

2.1 On-Body Interaction

On-body interaction has received considerable attention in recent years with representative systems such as PALMbit [74], Omni-Touch [22], Armura [24], or Botential [43] showing clear advantages over other modalities. Next, we focus on interactions involving the *palm*, *forearm*, and *upper arm*, in line with our scope.

2.1.1 Palm-based interactions. The palm is an easy-to-reach body part and a convenient support surface for input, including tapping, touching, grasping, and drawing. Due to these distinctive affordances, the palm has been largely used for novel interaction techniques, including interactions with mobile devices [19], wearables [68,69], remote displays [14], and in virtual environments [33,75]. One early result is PALMbit [74], a video projection system designed to be worn on the shoulder that transforms the user's palm into a touch interface for remote controlling electronic appliances, with selection performed by touching the fingertips. OmniTouch [22] adopted a similar design approach for the shoulder, but added short-range depth sensing to enable multitouch input on a diversity of everyday surfaces, including the palm. Depth-sensing technology has been popular for palm-based input [14,19,75]. For example, Gustafson et al. [19] used it for the “imaginary phone,” where users interact with their smartphones indirectly by tapping and sliding on their palms. Similarly, Dezfuli et al. [14] demonstrated PalmRC, an eyes-free palm-based input technique for TV control. Other body parts have also been instrumented to detect palm-based input. For example, Wang et al. [69] introduced Eye-Wrist, a wrist-mounted device consisting of an infrared micro camera and laser-line projector for eyes-free gesture input on the palm. PalmType [68] is a text entry technique for smartglasses that uses wrist-worn proximity sensors to detect finger taps on a QWERTY layout mapped onto the palm. Skinput [25] resolves the location of on-skin finger taps by analyzing mechanical vibrations propagating through the body, detected with a bio-acoustic sensing array worn as an armband. Zhang et al. [75] introduced ActiTouch, a technique for on-skin touch detection using a wristband radiofrequency emitter and detectors integrated into a head-mounted display.

2.1.2 Forearm-based interactions. Unlike the palm, the forearm provides a significantly larger surface for both input and output and, thus, new interactive opportunities. For example, Armura [24] enables interactions that involve the arms, either individually or in relation to each other, e.g., a crossing gesture of one arm above the other. Laput et al. [36] introduced “skin buttons” as icons rendered

on the user's skin, on the forearm and wrist, by tiny projectors integrated into a smartwatch. Tapping a skin button launches a corresponding application, e.g., a music player, on the smartwatch. Lin et al. [40] evaluated an interface for eyes-free tap input on the forearm and found that, on average, users can discriminate between seven locations on the forearm with the highest accuracy at elbow and wrist. Makino et al. [42,47] used armbands with reflective-type photoelectric sensors to measure slight skin deformations for swipes [42] and pull, push, and pinch [47] input on the forearm. Bergström-Lehtovirta et al. [6] examined how users map the surface of their forearms to a computer display, smartwatch, and AR headset, and delivered corresponding models of those mappings.

2.1.3 Upper-arm interactions. Our literature review revealed that upper-arm interactions have been considerably less studied compared to the palm and forearm. While the upper arm is more challenging to reach and not in direct sight as other arm regions, it presents several input opportunities. In this line, Weigel et al. [70] reported some user preference for upper-arm gestures (4.4% of the gestures elicited from 22 participants), such as grabbing the upper arm, yet the majority of the gestures involved the forearm and palm. Next, we turn to findings from gesture elicitation studies.

2.2 Gesture Elicitation of On-Body Interactions

We used the most recent systematic literature review on gesture elicitation [64], comprising 267 studies, to identify prior research on user-defined on-body input. We found only four studies [8,27,41,70], which focused on skin-based and bimanual hand gestures—two gesture categories sensibly different from our scope. For example, Weigel et al. [70] examined on-skin input to control mobile devices, and reported a majority of conventional multitouch gestures stemming from users' familiarity with touchscreens. Since there was no controlled condition for where gestures could be performed on the arm, their findings revealed that half of all gestures involved the forearm, followed by the hand, with only 4.4% using the upper arm. In contrast, our experiment in Section 4 is designed to elicit gestures indiscriminately across all palm, forearm, and upper arm regions with a considerably larger sample of participants—75 vs. 22 in [70]—and no restriction of physical contact with the opposite arm. Bostan et al. [8] also examined on-skin input, elicited from 19 participants, but restricted their investigation to the palm only, following an interaction metaphor of “hand as controller.” In a follow-up study [27], they compared on-skin with free-hand gestures, and reported the former as less physically demanding and more socially acceptable. Lastly, Lu et al. [41] explored “hand-to-hand gestures,” a class of bimanual input involving both hands moving and making physical contact, and proposed a design space comprising hand pose, motion, and touch location, informed by a referent-agnostic elicitation study. Although related to our scope, the gestures examined in [27,41] are restricted to the palm only, leaving gaps in design knowledge for forearm and upper-arm input.

2.3 A Knowledge Gap in User Preferences for On-Body Gestures

Our review of the scientific literature has revealed that, despite technological advances in developing interactive systems involving

the body for I/O, examination of user preferences for intuitive gestures has not been thoroughly conducted, leaving gaps in scientific and design knowledge. Furthermore, some arm regions, such as the upper arm, have been mostly neglected in this process. To address this aspect, we present in Section 4 an end-user elicitation study designed to gain insights into user preferences for intermanual deictics involving equally the *palm*, *forearm*, and *upper arm*. In the next section, we formalize intermanual deictics to highlight their unique qualities compared to other gesture types.

3 Intermanual Deictics

We position our research within the scope of bimanual gestures [29, 34], emphasizing input that is entirely defined by and requires the coordinated use of both hands, whether through synchronized action [13] or asynchronous movement [16]. However, the gestures we examine in this work present distinctive nuances in structure, articulation, and nature within the broader landscape of possible bimanual gesture types, thus necessitating their own class.

Whereas “bimanual” generally refers to the use of both hands in performing a task, it is too general a term and does not necessarily imply interaction occurring between the hands. Similarly, the terms “on-body” and “on-skin” do not fully capture our scope, as they imply physical contact—a requirement not necessary for our gestures. What sets these gestures apart from other bimanual and on-body input is that one arm serves as both the support and reference for the interaction performed by the other arm. This makes the gestures *intermanual* in structure, *asynchronous* and *asymmetric* in articulation, and *deictic* in nature, without requiring physical contact. Unlike typical bimanual gestures, intermanual gestures are defined by the two arms taking on specific roles—*support* and *implementer*,—e.g., the index finger of the right hand (the implementer) taps twice on the forearm of the left arm (the support). Unlike typical on-body input, intermanual gestures derive their meaning from a reference point, established either through physical contact or mid-air pointing, e.g., the index finger (the implementer) draws a circle the distal region of the opposite forearm (the support).

In this context, we emphasize the need for distinct terminology to effectively navigate our scope, for which we adopt *intermanual deictics* to refer to articulations that prioritize the referential relationship between the two arms. To formalize intermanual deictics, we capitalize on existing gesture taxonomies and frameworks in Human-Computer Interaction, Motor Control, and Psychology that center on skilled bimanual action [18], body-centric interaction [61,67], gesture form [44], gesture function [32,53], and the sensorimotor attributes of gestures [30]; see Figure 2 for an overview. For instance, according to Wagner et al.'s [67] design space for body-centric interactions, intermanual deictics can be characterized as relative to the body, unrestricted by environmental constraints, involving one arm that acts and another that is affected, and not necessarily requiring a physical contact. In terms of the articulation space relative to the body [61], intermanual deictics are performed within the personal space when involving physical contact and within the peripersonal space when articulated near the opposite arm without touching it. According to Guiard's [18] kinematic chain model, intermanual deictics are bimanual asymmetric gestures in which the differentiated motor activities of the two arms serve to

Reference	Overview of gesture taxonomy/framework	Differentiation criteria	Gesture class			
			Intermanual deictics	On-body/skin gestures	Hand-to-hand gestures	Bimanual gestures
Wagner <i>et al.</i> (2013)	A body-centric interaction design space focusing on the relationship between the user's body and the environment during gesture input	Input relative to body	Yes	Yes	Yes	Not required
		Involved body part	Hand	Hand	1-2 hands	1-2 hands/arms
		Affected body part	Opposite arm	Any body part	1-2 hands	0-2 hands/arms
		Physical contact	Not required	Required	Required	Not required
		Skin contact	Not required	Required for on-skin	Required	Not required
Karam & schraefel (2005)	Taxonomy of gesture styles for HCI: gesticulation, deictic, manipulative, semaphoric, sign language, mixed	Gesture style	Deictic-first, Manipulative, Semaphoric, Mixed	Deictic, Manipulative, Semaphoric, Mixed	Deictic, Manipulative, Semaphoric, Mixed	Deictic, Signs, Manipulative, Semaphoric, Mixed
Quek <i>et al.</i> (2002)	Taxonomy of gestures based on purpose in multimodal interaction	Gesture purpose	Semaphoric, Manipulative	Semaphoric, Manipulative	Semaphoric, Manipulative	Semaphoric, Manipulative
Vatavu (2023)	Taxonomy of gestures according to the index finger-centric perspective and the body scale of input	Body-level articulation space	Personal space, Peripersonal space	Personal space	Personal space	Personal space, Peripersonal space
		Referenced body part	Opposite arm	Any body part	Opposite hand	Not required
McNeill (1992)	Taxonomy of gestures articulated in relation to speech and a coding procedure for describing gestures according to their type, form, meaning, and location in gesture space, from center-center to extreme periphery	Hand form	2DH*	2DH*	2SH, 2DH*	2SH, 2DH*
		Direction of motion	2DM**	2DM**	2SM, 2DM**	2SM, 2DM**
		Hand motion	Toward the body (opposite arm)	Toward the body (any body part)	Toward the body, away from, parallel to body	Toward the body, away from, parallel to body
		Place in gesture space	Center, Periphery	Center-Center, Center, Periphery, Extreme Periphery	Center-Center, Center	Center-Center, Center, Periphery, Extreme Periphery
Guiard (1987)	Kinematic chain model for skilled bimanual action, emphasizing the different roles of the hands and the intermanual division of labor during task performance	Involves both arms	Yes	Not required [†]	Yes	Yes
		Symmetry	Asymmetric	Asymmetric	Symmetric, Asymmetric	Symmetric, Asymmetric
		Body spatial reference	Yes	Yes	Not required	Not required
		Arm spatial reference	Yes	Not required [†]	Not required	Not required
		Hand role distinction	Yes	Not required [†]	Not required	Not required
Jones & Lederman (2006)	The sensorimotor continuum: tactile sensing (hand receives information), active sensing (hand collects information), prehension, non-prehensile movements (pointing)	Sensorimotor function of the hand	Tactile sensing, Active haptic sensing, Prehension, Non-prehensile skilled movements	Tactile sensing, Active haptic sensing, Prehension	Tactile sensing, Active haptic sensing, Prehension	Tactile sensing, Active haptic sensing, Prehension, Non-prehensile skilled movements

*2SH=two same hands, 2DH=two different hands; **2SM=two same motion, 2DM=two different motion; [†]If input is outside the arm.

■ Taxonomy/framework from Human-Computer Interaction ■ Psycholinguistics ■ Motor control ■ Neuropsychology

Figure 2: Intermanual deictics compared to on-body/skin, hand-to-hand, and bimanual gestures. Note: blue cells highlight differences based on gesture taxonomies and frameworks in HCI [32,53,61,67], Psychology [30,44], and Motor Control [18].

specify steady states (the support) and create changes (the implementer). Furthermore, this model posits a postural-manipulative division of action, where the contribution of the support arm begins earlier than that of the implementer, which finds its spatial references in relation to the support. In this process, intermanual deictics exhibit two distinct motion patterns (2DM) and hand poses (2DH), and are performed in the center and periphery zones of the gesture space, according to McNeill's [44] notations and classification of bimanual gesture articulation.

These characteristics specify a distinctive class of gestures featuring asynchronicity, a deictic nature, and support-implementer

referential action. Unlike on-body/skin gestures [4,57,64], intermanual deictics do not necessarily require physical contact, e.g., the index finger can perform a mid-air tap above the opposite arm. Additionally, they are not limited to skin manipulation [70], e.g., a grasp can be performed on the upper arm covered by clothing. Unlike hand-to-hand gestures [41], intermanual deictics do not require a mid-air articulation component to convey meaning and are not limited to the hands only; instead, they can address the entire arm. These characteristics warrant a thorough examination of this class of gesture input to identify new opportunities for interactive systems. In the next section, we present a study specifically designed to uncover users' preferences for intermanual deictics.

4 Experiment

We conducted a controlled experiment to collect users' preferences for gesture input relative to the opposite arm. An institutional ethics protocol was in place at the Ștefan cel Mare University of Suceava for our experiment implementing the end-user gesture elicitation method [73], in its most recent formalization [62] based on dissimilarity-consensus analysis [60].

4.1 Participants

Seventy-five participants, all young adults aged 22 to 35, were recruited through mailing lists and convenience sampling from the university's student body and teaching staff. Of these, sixty-one self-identified as male and fourteen as female. No compensation was provided to participants, except for the opportunity to learn about new interactive technologies involving the human body during the experiment. All participants were regular smartphone users and, thus, familiarized with touch input. We randomly assigned the participants to one of three equally-sized groups corresponding to different conditions of intermanual deictics performed relative to the opposite *palm*, *forearm*, and *upper arm*, respectively.

4.2 Design

Our experimental design was mixed with two factors:

- **REGION**, nominal variable with three categories—*palm*, *forearm*, and *upper arm*, administered between participants, representing the region on the support arm in relation to which gesture input was performed.
- **REFERENT**, nominal variable with ten categories, administered within participants, representing common system commands—"next," "previous," "increase," "decrease," "OK," "cancel," "menu," "help," "home," and "undo"—selected from the most influential end-user gesture elicitation studies [31,35,37,51,55,73], according to the systematic reviews in [64,65].

4.3 Procedure

The participants were asked to propose gestures, relative to the opposite arm, to effect the ten referents. The instructions were minimal since our goal was to uncover intuitive preferences for intermanual deictics, e.g., "Propose a gesture, relative to the opposite *forearm*, that you consider intuitive and suitable for executing *next*, meaning moving to the next item in a list." We did not use or imply any gesture recognition technology to avoid imposing constraints on the participants' proposals. Furthermore, as in prior elicitation studies [70], the participants were allowed to freely choose between their dominant and non-dominant hands to act as implementer and support. The order of **REFERENT** was randomized per participant. All gestures were performed with the participants seated, and were recorded on video. The duration of the experiment for each participant ranged from 30 to 40 minutes, which included a welcome and briefing about intermanual deictics, providing instructions, and the actual gesture elicitation procedure just described.

4.4 Measures

We used the video recordings to extract characteristics of our participants' gestures through the prism of three categories of measures

targeting specific aspects of gesture articulation, intermanuality, and consensus among participants, as follows.

4.4.1 Measures of gesture articulation. The following measures, adopted from prior work that examined users' preferences for gesture input [1,7,15,55], are designed to differentiate gesture articulations according to their type, scale, and complexity:

- **GESTURE-TYPE**, with six categories—*touch*, *grasp*, *pose*, *stroke*, *hover*, and *mixed*—was inspired from [1,4,7,22]. The first four categories represent gestures involving physical contact with the opposite arm, ranging from a brief tap to a prolonged stroke representing symbolic input. The *hover* category represents non-contact gestures, for which we drew inspiration from [1,22]. In these gestures, one hand points to or performs a pose or motion near, but not touching, the support arm. Finally, *mixed* gestures involve a combination of the previous categories, such as a tap on the index finger followed by drawing the "question mark" symbol on the palmar surface.
- **GESTURE-SCALE**, with three categories—*small* (gestures targeting a specific point or points, e.g., a tap on the middle finger or a three-finger tap in the palm for "next"), *medium* (gestures covering an area up to 50% of the support region, e.g., drawing a circle on the distal forearm for "undo"), and *large* (gestures using more than 50% of the support region, e.g., a swipe from elbow to shoulder for "increase"). These categories were inspired by Weigel et al.'s [70] contact area for on-skin input and Gheran et al.'s [15] scale measures.
- **GESTURE-COMPLEXITY**, comprising two categories—*simple* and *compound*—adopted from [15,55]. Simple gestures are standalone movements with inherent meaning, e.g., a circle for "undo," whereas compound gestures can be decomposed into individually meaningful gestures, e.g., a tap and a circle.

4.4.2 Measures of intermanual articulation. To characterize the various ways in which intermanual deictics can be implemented by involving the implementer and support arms, we measured:

- **IMPLEMENTER** refers to the region of the moving arm used to perform the gesture on the support. For example, touch input might involve the index finger, both the index and middle fingers, or all fingers.
- **SUPPORT** specifies the region on the opposite arm referenced by the implementer, e.g., the elbow in the *forearm* condition. Informed by categorizations used for on-body input [4,5,25,70], we coded **SUPPORT** into four high-level categories for each of the *palm*, *forearm*, and *upper arm* regions; see Figure 4c. On the *palm*, we differentiate among the palmar surface, fingers, interdigital spaces, and wrist. On the *forearm*, we distinguish among the distal forearm (near the wrist), mid-forearm, proximal forearm (near the elbow), and elbow. On the *upper arm*, we differentiate among the distal upper arm (near the elbow), mid upper arm, proximal upper arm (near the shoulder), and shoulder. While other studies, with different goals, have explored these regions in various detail—finger phalanges and joints [5], areas of the palmar surface [22,75], or landmarks across the palm [5,20,58]—we preferred only four zones in each **REGION** for simplicity and ease of coding. Moreover, there are known benefits in using

fewer regions for on-body input, e.g., Lin et al. [40] found that five locations, from wrist to elbow, can be quickly reached during eyes-free input with near 100% accuracy.

- **HANDEDNESS** indicates the roles of the two arms, reflecting the percentage of instances where the left or right arm functioned as either the implementer or the support.

4.4.3 Measures of agreement. To understand the similarity among the intermanual deictics elicited from our participants, we employed agreement (AR_ϵ) and coagreement (CR_ϵ) rate measures, computed according to the most recent formulation of the elicitation method and the “computer” model of agreement analysis [62]:

- **AGREEMENT-RATE**, AR_ϵ [60,62], reports the level of agreement in a set of gestures:

$$AR_\epsilon(R) = \frac{\sum_p \sum_{q \neq p} [\delta(p, q) \leq \epsilon]}{N(N-1)} \cdot 100\% \quad (1)$$

where N is the number of gestures elicited for referent R , δ is a function for evaluating the dissimilarity between any two gestures p and q , and ϵ a positive value representing the tolerance below which two gesture descriptions are similar enough to be considered equivalent, according to the dissimilarity-consensus method [60]. AR_ϵ takes values between 0 and 100, representing the percentage of pairs of participants in agreement. To evaluate δ , we represented gestures with their **GESTURE-TYPE**, **GESTURE-SCALE**, and **SUPPORT** attributes¹ as $p = \{p_k, k=1..3\}$, e.g., p may be (*touch*, *small*, *palmar surface*) for a tap on the palmar surface, and we used the expression in [62]:

$$\delta(p, q) = 1 - \sum_{k=1}^3 w_k S_k(p_k, q_k) \quad (2)$$

where $S_k(p_k, q_k)$ is the per-attribute similarity between any two values of the k -th categorical attribute and w_k is the weight assigned to the k -th attribute, according to [39]:

$$S_k(p_k, q_k) = \begin{cases} 2 \log(\pi_k(p_k)) & p_k = q_k \\ 2 \log(\pi_k(p_k) + \pi_k(q_k)) & \text{otherwise} \end{cases} \quad (3)$$

$$w_k = \frac{1}{\sum_{k=1}^d \log(\pi_k(p_k)) + \log(\pi_k(q_k))} \quad (4)$$

In Eqs. 3 and 4, $\pi_k(x)$ is the sample probability of the k -th gesture attribute to take value x , estimated from the collected data, e.g., in the above example, $\pi_1(\textit{touch})=.288$, $\pi_2(\textit{medium})=.431$, and $\pi_3(\textit{palmar surface})=.231$; see Figure 3.

- **COAGREEMENT-RATE**, CR_ϵ [62], reports the coagreement among gestures elicited in different **REGION** conditions:

$$CR_\epsilon(R_1, R_2) = \frac{\sum_p \sum_q [\delta(p, q) \leq \epsilon]}{N^2} \quad (5)$$

where p and q enumerate gestures elicited for referents R_1 and R_2 in different conditions, e.g., *pal* and *forearm*.

¹We excluded **IMPLEMENTER** from the gesture description in this analysis because our results showed that the index finger was highly preferred, being used in 94.3% of the elicited gestures; see Figure 4 and the discussion from Section 5. We also excluded **GESTURE-COMPLEXITY** because of the large prevalence of *simple* (88.9%) over *compound* (11.1%) gestures; see Figure 3c and Section 5 for a discussion of these results. In contrast, the **GESTURE-TYPE**, **GESTURE-SCALE**, and **SUPPORT** measures showed the largest variation in our data and were thus used for dissimilarity analysis.

4.5 Statistical Analysis

To analyze categorical and ordinal variables with polytomous responses in our mixed-design experiment, e.g., **GESTURE-TYPE** and **GESTURE-SCALE**, we employed Cumulative Link Mixed Models [11] with maximum likelihood estimates of the parameters provided by the Laplace approximation method [12] with participants nested within **REGION**, and **REFERENT** treated as a random effect. We also used Wilcoxon tests to compare observed percentages against expected ones. Lastly, we employed growth rates r and dissimilarity-consensus τ -C logistic modeling [60,62] for agreement analysis.

5 Results

We report results on users’ preferences for intermanual deictics involving the opposite *palm*, *forearm*, and *upper arm*, based on a dataset of 750 gestures collected from 75 participants.

5.1 Gesture Type

We observed a high prevalence of *strokes*, accounting for 62.4% of all the elicited gestures, followed by *touch* input at a notable distance with 28.8% occurrence. The other gesture categories collectively accounted for just 8.8% of all the elicited gestures, wherein 2.0% were *mixed*; see Figure 3a. The observed percentages of **GESTURE-TYPE** significantly deviated from those expected by chance ($p < .001$), except for *touch* ($V=1674$, $p=.188$), while both *strokes* and *touch* gestures were significantly more prevalent than all other gesture categories ($p < .001$, FDR p -value corrections applied).

We found a statistically significant effect of **REGION** on **GESTURE-TYPE** ($\chi^2_{(2)}=7.235$, $p=.027$) with post-hoc tests (FDR p -value adjustments applied) revealing differences between the *palm* and *forearm* ($p=.019$), and *palm* and *upper arm* ($p=.001$). The *palm* exhibited the highest percentage of *touch* gestures (49.6%), which decreased by a factor of three to 19.6% and 17.2% for the *forearm* and *upper arm*. Additionally, the *palm* showed similar percentages of *stroke* (44.8%) and *touch* (49.6%) gestures, which diverged considerably for the *forearm* and *upper arm*. The other gesture types were little represented. For example, *hover* gestures, performed without making contact with the support arm, accounted for only 5.2% of all the elicited gestures, with the highest occurrence observed in the *forearm* condition (10.0%) and the lowest in the *upper arm* (0.8%).

Figure 3e shows that the distribution of elicited gestures by their type, observed overall, is also consistent across the individual referents, e.g., the dichotomous referents “next”–“previous” and “increase”–“decrease” were assigned gestures with the same attributes. Three notable exceptions deviate from the general trend: “home,” “OK,” and “menu” involved more touches and fewer strokes.

5.2 Gesture Scale

The elicited gestures were uniformly distributed in terms of scale, with no significant differences among the percentages of *small*, *medium*, and *large*-scale gestures ($p > .05$, FDR p -value adjustments applied), ranging from 27.3% to 43.1%; see Figure 3b. Yet, both the percentages of *small* and *medium*-scale gestures turned out significantly different from those expected by chance (29.6%, $V=1011.0$, $p=.028$ for *small* and 43.1%, $V=1862.0$, $p=.020$ for *medium*). Overall, the gestures utilized an area on the support arm (70.4% of the

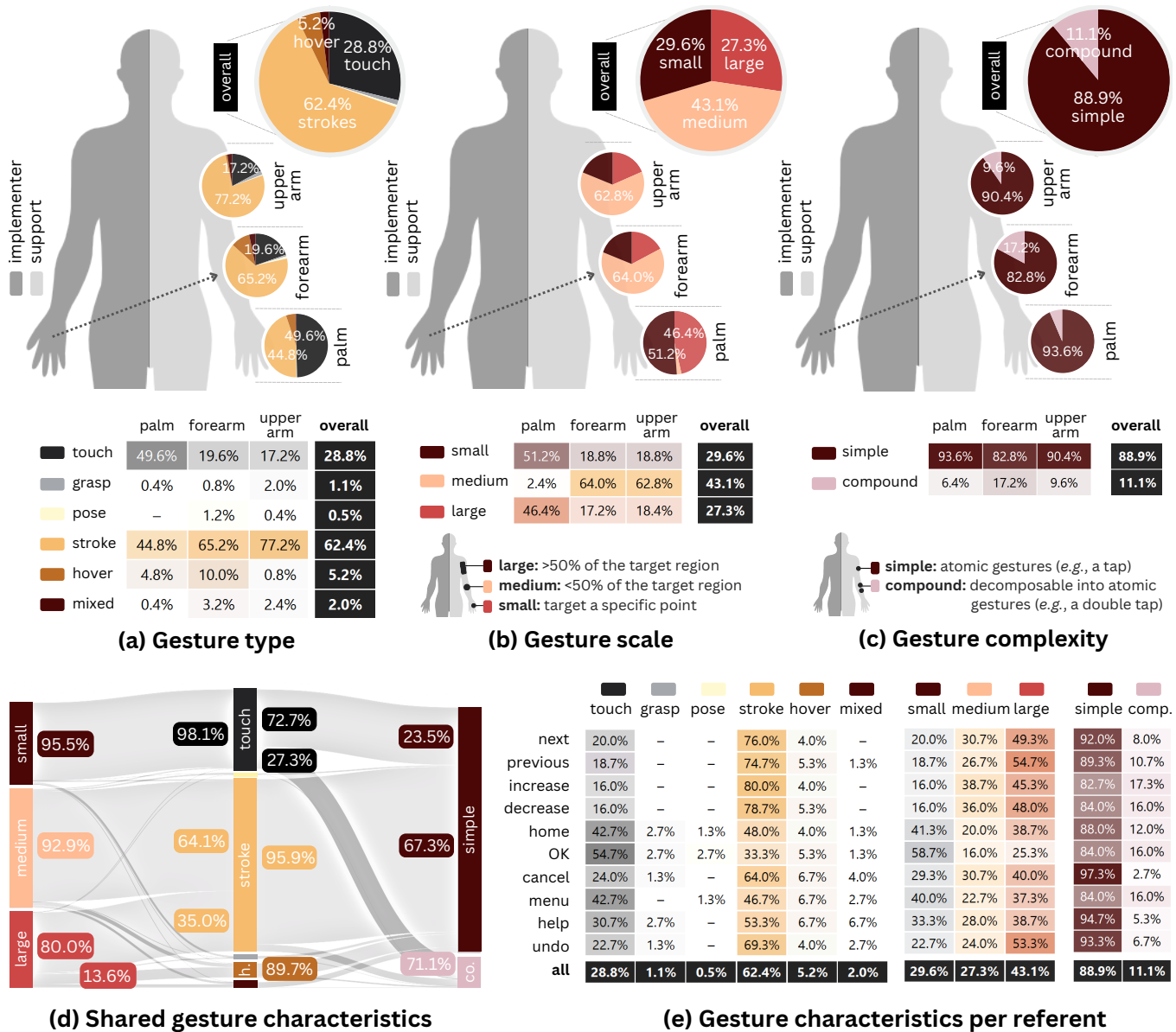


Figure 3: An overview of the GESTURE-TYPE, GESTURE-SCALE, and GESTURE-COMPLEXITY characteristics of the intermanual deictics elicited in our study. Note the large preference for stroke gestures (a), relative uniform distribution of gesture scales (b), propensity for simple gestures (c) across all gesture types (d), overall similar input behavior for intermanual deictics involving the forearm and upper arm (a-c), and the overall consistent distribution of gesture characteristics across referents (e).

cases) rather than a specific point (29.6%). We also found a significant effect of REGION on GESTURE-SCALE ($\chi^2_{(2)}=11.759, p=.003$), confirmed by post-hoc tests for all pairs of conditions ($p<.001$) except for forearm and upper arm ($p=.882, n.s.$); see Figure 3b. The palm condition stands out with similar percentages of small and large-scale gestures (51.2% and 46.4%), indicating that our participants either targeted specific points or used more than half of the palm’s surface during their gesture articulations. In contrast,

medium-scale gestures were most prevalent in the forearm and upper arm regions (64.0% and 62.8%). The large majority of small-scale gestures were represented by touch input, whereas medium and large-scale gestures were mostly implemented with strokes; see Figure 3d. Additionally, Figure 3e shows that the distributions of GESTURE-SCALE percentages are generally similar across different referents with three exceptions represented by “home,” “OK,” and “menu,” which received more small-scale gestures.

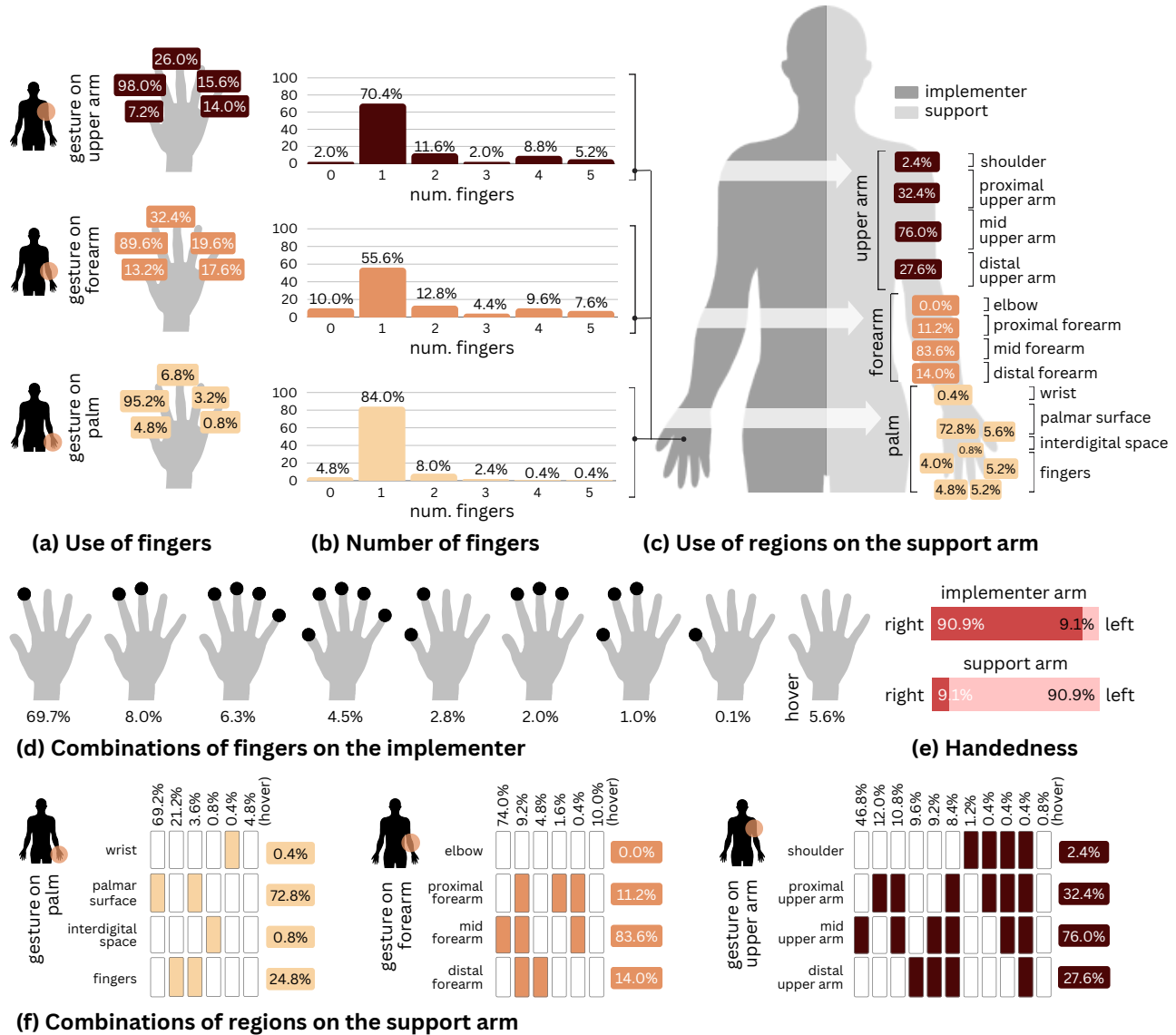


Figure 4: An overview of IMPLEMENTER and SUPPORT results. Note the large preference for the index finger of the implementer (a,b,d) and the prevalence of the palmar region, mid forearm, and mid upper arm of the support arm (c,e).

5.3 Gesture Complexity

Our participants overwhelmingly preferred *simple* (88.9%) over *compound* (11.1%) gestures ($p < .001$), with both percentages significantly deviating from those expected by chance ($V=2848.5$ and $V=1.5$, $p < .001$, respectively); see Figure 3c. We also found a significant effect of REGION on GESTURE-COMPLEXITY ($\chi^2_{(2)}=6.852$, $p=.033$) with post-hoc tests (FDR p -value adjustments applied) revealing statistically significant differences only between *palm* and *forearm* ($p=.006$). Most of the *compound* gestures were observed in the *upper arm* condition as variations of *touch* input, with a considerably smaller percentage involving *strokes*; see Figure 3d for details. Figure 3e shows that the distribution of the gestures by complexity, observed overall, is consistent across individual referents.

5.4 Aspects of Intermanual Gesture Articulation

We found an asymmetrical HANDEDNESS distribution of the IMPLEMENTER and SUPPORT roles of the two arms, with the right arm predominantly used as the implementer in 90.9% of the elicited gestures, and the left arm in 9.1%. These percentages align with the estimated left-handedness prevalence in humans, of about 10%, as reported in the meta-analysis by Papadatou-Pastou et al. [49]. Next, we detail on specific IMPLEMENTER and SUPPORT regions.

At the level of IMPLEMENTER, we observed intermanual gestures involving from one to five fingers ($M=1.5$, $SD=0.8$, $Mdn=1$) in contact with the support arm; see Figures 4a and 4b for finger use percentages and finger count histograms according to each REGION. The majority (70.0%) of the elicited gestures involved one

finger only, while 10.8% used combinations of two fingers, and 4.4% involved all five fingers, respectively; see Figure 4d. The overwhelmingly strong preference for the index finger (94.2%) is readily apparent in Figures 4a and 4d, followed by the middle finger at a considerable distance (21.7%). All the *hover* gestures and a small portion of the *mixed* gestures, respectively, accounting for 5.6% of all the elicited gestures, involved no physical contact at all with the support arm. For intermanual deictics involving the *palm*, our participants used the fewest number of fingers ($M=1.1$, $Mdn=1$), with 84% of the proposed gestures involving one finger only. In contrast, the *forearm* condition saw the highest finger usage ($M=1.7$, $Mdn=1$), with 34.4% of the elicited gestures involving at least two fingers and 17.2% four or five fingers. For example, a pinch gesture performed with the thumb and index fingers was proposed by one participant to effect “increase” and “decrease” on the forearm, whereas another participant performed “undo” with a swipe towards the ulnar side of the upper arm using the index, middle, ring, and little fingers. Examples of five-finger gestures include touching the palmar surface with all the fingers for “home,” grasping the upper arm for “help,” or swiping towards the wrist with all five fingers for “menu.”

We found different preferences for the *SUPPORT* region on the opposite arm relative to which gestures were performed; see Figure 4c. In the *palm* condition, gestures predominantly targeted the palmar surface (74.4%) followed by the fingers (24.4%), with similar distributions observed across individual fingers, between 4.3% for the thumb and 5.4% for the little finger. For example, one participant proposed touching the index finger to effect “OK” and the little finger for “cancel,” while another participant swiped on the ring finger in opposite directions to effect “increase” and “decrease.” In the *forearm* condition, the majority of the gestures employed the mid forearm region (74.5%), whereas in the *upper arm* condition, gestures predominantly involved the mid upper arm (55.4%). For example, a swipe towards the radial side of the forearm was proposed for “next.” The joints of the support arm—wrist, elbow, and shoulder,—were rarely used, with only 0.4%, 0.0%, and 0.9% of the proposed gestures targeting them. Example gestures that used these regions comprise touching the wrist or swiping on the shoulder for “menu.” These findings correspond to intermanual deictics being performed from a seated position, for which we observed that the support arm was held approximately perpendicular to the body (portrait mode) in 56.0% of the articulations, angled relative to the body (diagonal mode) in 33.3%, and held relatively parallel to the body (landscape mode) in 10.7% of cases. Figure 4f shows combinations of various support regions targeted in conjunction, e.g., the fingers and palmar surface were used in 3.6% of the gestures in the *palm* condition, and the proximal and mid upper arm were used together in 10.8% of the gestures involving the *upper arm*.

5.5 Consensus Gesture Set

To understand the level of consensus among our participants' gesture articulations, we computed the agreement rate measure (AR_ϵ) for each combination of $REGION \times REFERENT$ using the procedure described in Subsection 4.4.3. Figure 5, top shows agreement rate results for the tolerance level $\epsilon=0$, meaning that two intermanual deictic gestures are considered equivalent if and only if they exhibit the same $GESTURE-TYPE$, $GESTURE-SCALE$, and $SUPPORT$ attributes.

Using this procedure, we found an overall agreement rate of 24.5% in the *palm*, 34.1% in the *forearm*, and 20.2% in the *upper arm* conditions. Figure 5, bottom shows the relationships between AR_ϵ and ϵ for each $REFERENT$, representing similarity evaluations under less strict tolerance requirements ($\epsilon>0$), following analysis recommendations from [60]. Logistic modeling applied to these relationships revealed a good fit with average growth rates r of 14.9 ($SD=10.4$), 18.9 ($SD=5.0$), and 16.0 ($SD=6.3$) in the *palm*, *forearm*, and *upper arm* conditions and no significant effect of $REGION$ ($\chi^2_{(2)}=5.000$, $p=.082$), showing similar growth behavior of AR_ϵ with increasing ϵ levels.

Figure 6 presents a consensus set of intermanual deictics, based on the most conservative threshold ($\epsilon=0$), involving all three regions on the opposite arm. In this figure, the *implementer* and *support*, key to intermanual deictics, are visually emphasized through color, contrasting with the gray background of the other, non-involved body parts. Two choices are offered for each referent: the winning gesture, shown on the first row in each region, which is based on the most frequently elicited gesture articulations for that referent, along with an alternative gesture, shown in the second row in each region, representing the second most frequently observed articulation in our dataset. For example, the “next” and “previous” referents were mostly performed in the *palm* condition with swipes toward the ulnar and radial sides (the first-option gestures in Figure 6, first row), but some participants preferred performing taps on the little and ring fingers (our second gesture options, presented in Figure 6, second row). The colored boxes shown on the right side of each gesture encode its attributes, e.g., the “swipe toward ulnar side” gesture proposed to effect “next” is classified as a large-scale (L) stroke (St) involving the palmar (Pa) surface. The alternative for “next” in our set is “tap on the little finger,” a small-scale (S) touch (T) gesture on the finger (F). To complement these results, though not contributing to the consensus set, Figure 7 illustrates examples of *hover* gestures identified in our study. Given their rarity (5.2%), these gestures are presented solely for exemplification purposes, and were selectively chosen from our dataset. Nonetheless, note articulation similarities with the contact-based gestures from Figure 6.

Directional swipes are prevalent in the consensus set for the four referents with a directional connotation—“next,” “previous,” “increase,” and “decrease,”—and were consistently proposed across all three regions. Other strokes, such as letters, e.g., “X” for “cancel,” and symbols, e.g., “checkmark” for “OK” or “question mark” for “help,” were also observed across all regions. Variations of tap-based input are equally represented in our set. For example, in the *palm* condition, participants often tapped with a single finger at different locations, such as at the bottom of the palm for “menu.” In the *forearm* and *upper arm* conditions, tap gestures included multi-finger taps, such as four-finger or three-finger taps for “menu.” Overall, these preferences leverage intuitive connotations in the referents while exploiting participants' familiarity with touch-based interactions, prevalent on personal digital devices.

We also observed instances where identical gestures were occasionally proposed for different referents by different participants, e.g., tapping in the palm center for both “home” and “menu” (Figure 6, top two rows) or drawing a circular shape for both “undo” and “cancel” (Figure 6, last two rows). To find out more, we computed coagreement rates CR_ϵ , following the procedure described in

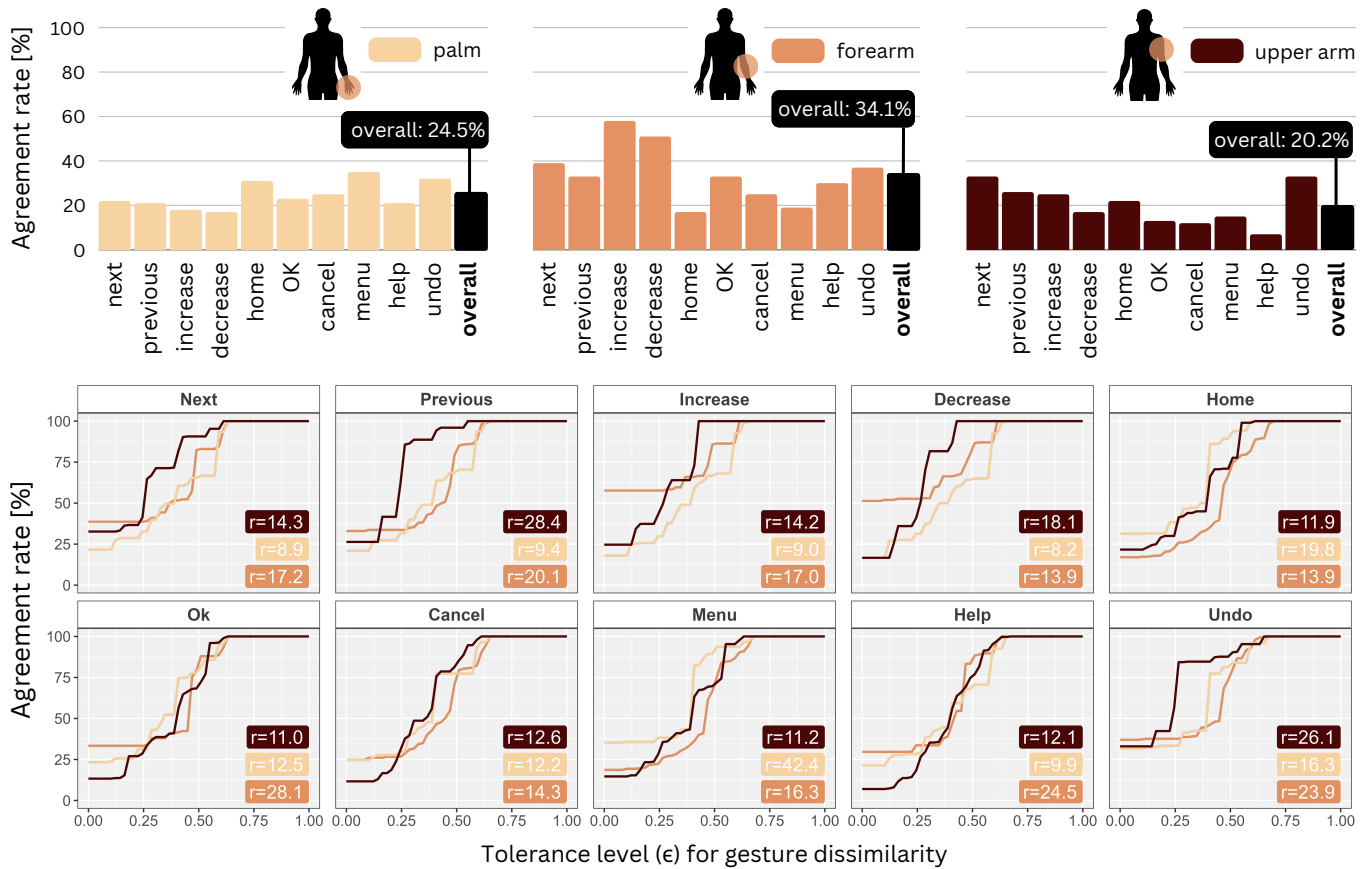


Figure 5: Agreement rates AR_{ϵ} [62] computed for the tolerance level $\epsilon=0$ (top) and growth rate dissimilarity-consensus curves [60] (bottom), illustrating the effect of ϵ on the agreement among elicited gestures. Note the similar behavior of the AR_{ϵ} dependence on ϵ across various referents, confirmed by non-significant differences among the average growth rates r in each REGION.

Subsection 4.4.3, which quantify the degree of similarity between intermanual deictic gestures elicited for different referents; see Figure 8. Notable is the considerably higher coagreement rate observed for the *forearm* and *upper arm* (39.2%) compared to the *palm* and *forearm* (14.1%) and *palm* and *upper arm* (15.9%), respectively, revealing that the *forearm* and *upper arm* elicited more similar gestures, most likely due to their structural and area size similarities compared to the palm. The coagreement rates in the diagonals of the matrices in Figure 8 are especially interesting since they show how the same referent, e.g., “next” or “undo,” received gestures having the same attributes, although they were performed in different regions. These findings suggest important implications regarding the interchangeability of intermanual deictics across different arm regions, which we further explore in Section 6.

6 Design Implications for Interactions Incorporating Intermanual Deictics

Our findings revealed user preferences for intermanual deictics centered around touch and stroke input, exhibiting similar agreement rates across the opposite *palm*, *forearm*, and *upper arm* regions, with larger coagreement observed between the latter two. Next,

we capitalize on our empirical findings to outline a set of design principles and corresponding practical implications for interactions that incorporate intermanual deictics.

① **Design interactions based on intermanual deictics that leverage the entire support arm, from fingers to shoulder.** Prior work on on-body input has focused on gestures performed at specific arm regions, such as the palm [8,27,41], or treated the arm as a whole [70], without accommodating alternative user preferences for input involving other regions, not designer-chosen, or multiple regions of the arm. In our study, which indiscriminately addressed three distinct regions, we found that gestures with similar attributes emerged across them. **Supporting data:** The analysis from Subsection 5.5 revealed comparable average agreement rates, from 20.2% to 34.1%, and comparable growth rates, from 14.9 to 16.0, for input involving the palm, forearm, and upper arm. **Practical implications:** (I₁) *Design intermanual deictics that fully utilize the available surface area of the support arm for input.* For example, controlling a music application could utilize the entire arm—tapping on the palm to play and pause, swiping on the forearm to skip to the next song, and pinching in and out on the upper arm to adjust the volume—where the various controls are evenly distributed across

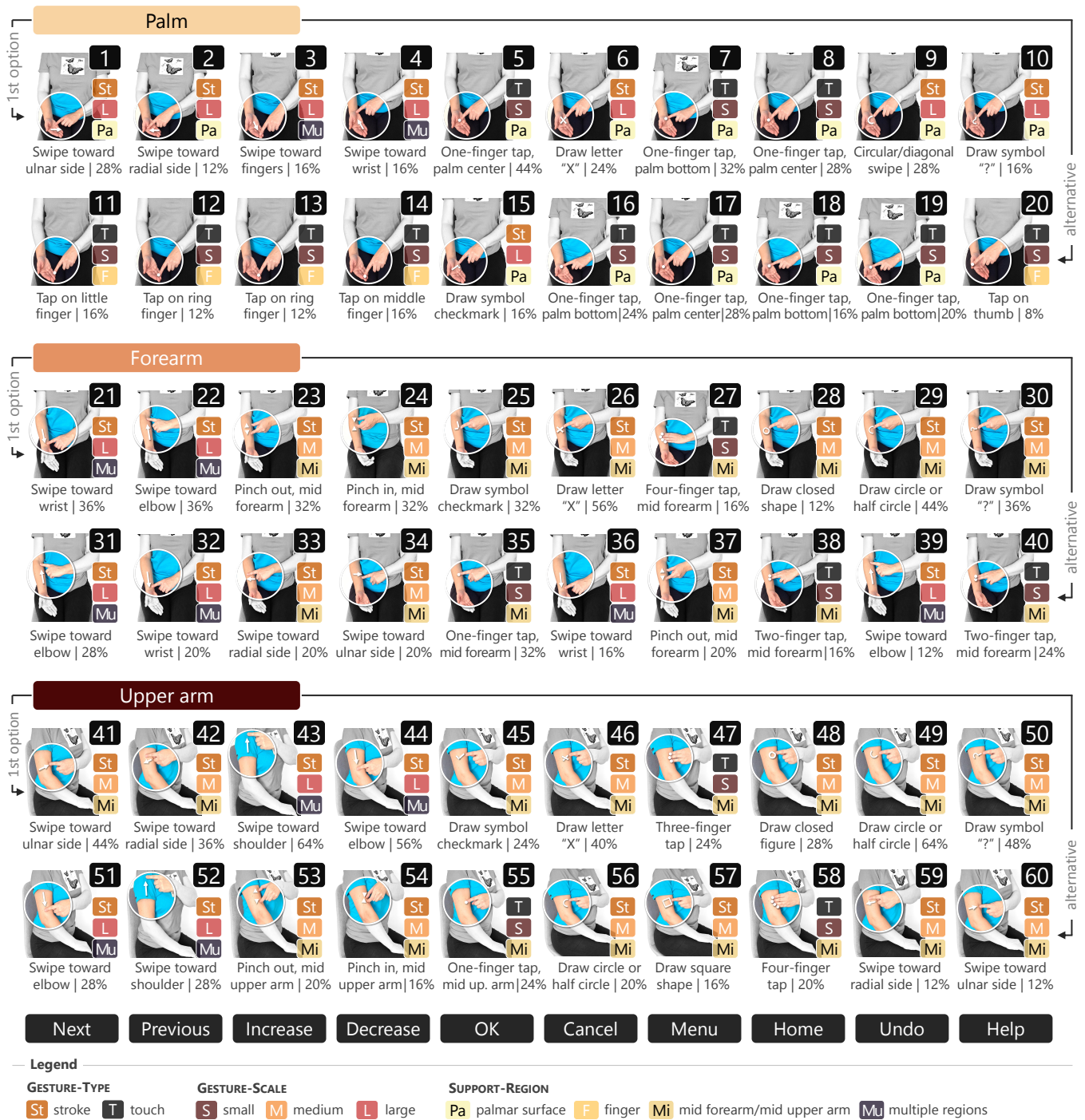


Figure 6: Consensus gesture set. Notes: two options, the winning gesture and the next-best alternative, are presented for each referent; the colored boxes indicate gesture attributes, e.g., a large-scale stroke in the palmar surface is represented as St-L-Pa.

the arm. (I₂) Foster a mental model of interaction involving intermanual deictics where different regions on the support arm offer equal opportunities for input. For example, provide recommendations for users to switch between different arm regions when performing

the default gestures provided by the application, and encourage them to create personalized gestures without prioritizing specific regions of the opposite arm.

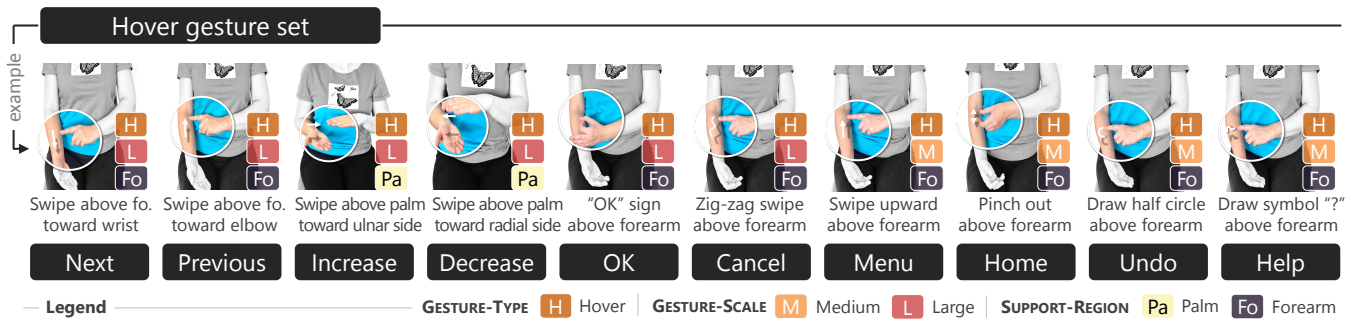


Figure 7: Illustrative examples of hover intermanual deictics. Note similarities with the contact-based gestures in Figure 6.

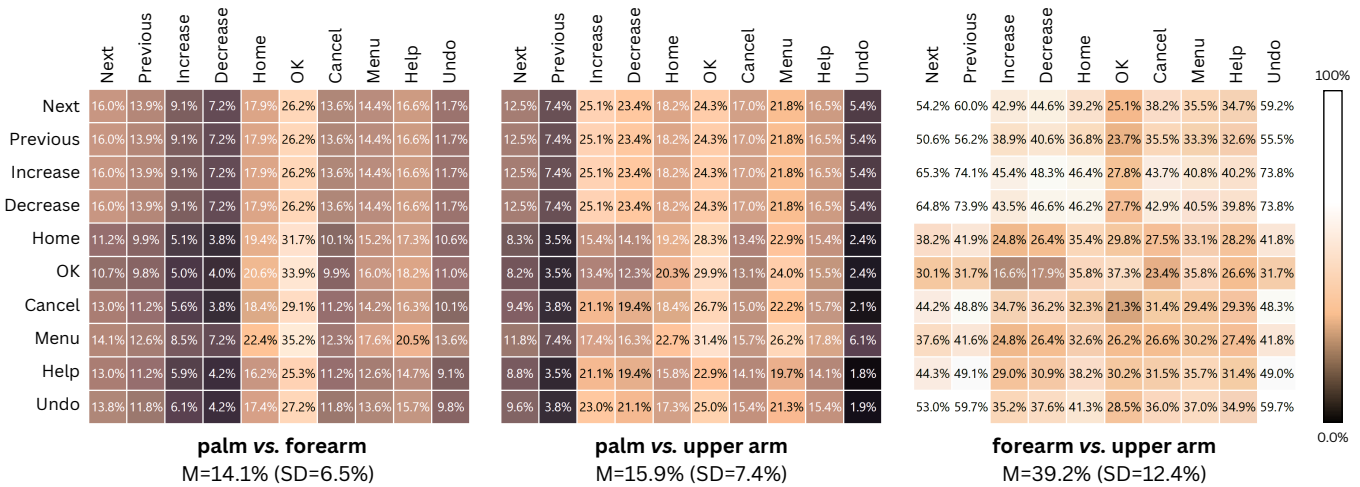


Figure 8: Coagreement rates (CR_ϵ) computed for the tolerance level $\epsilon=0$, showing users' preferences for intermanual deictics across the *palm*, *forearm*, and *upper arm* regions.

② Use the forearm and upper arm interchangeably for input. The forearm and upper arm present similarities in form, structure, and size, indicating their potential to serve alike as support references for intermanual deictics. The shared characteristics of the gestures elicited in these regions suggest users' perception of such similarities. **Supporting data:** The GESTURE-TYPE and GESTURE-SCALE measures revealed many similarities across the gestures involving the forearm and upper arm compared to the palm. For instance, touch input comprised 19.6% and 17.2% of the gestures on the forearm and upper arm, vs. 49.6% on the palm. Furthermore, medium-scale gestures amounted to 64.0% and 62.8% on the forearm and upper arm, compared to just 2.4% on the palm (Figures 3a and 3b). These similarities were also present at the level of the individual referents (Figure 3e). **Practical implications:** (I₃) Reuse intermanual deictics designed for the forearm on the upper arm and vice versa. For example, directional swipes or pinches on the forearm to navigate through a list of items could also be recognized to effect the same command when performed on the upper arm. (I₄) Favor user personalization of intermanual deictics by allowing flexibility in where input is performed, enabling the same gesture to be used interchangeably involving both the forearm and upper arm. For example, a pinch gesture configured to adjust the volume on the

upper arm could also be recognized on the forearm, allowing users to choose the most comfortable location as per their preferences or specific contexts of use.

③ Favor intermanual input involving the central areas of the palm, forearm, and upper arm. Our findings revealed that intermanual deictics were predominantly concentrated in the central area of each arm region, likely due to ease of reach. **Supporting data:** Of all the elicited gestures in the palm condition, 72.8% were performed on the palmar surface; 83.6% of the gestures elicited relative to the forearm involved the mid forearm; and 76.0% of the upper-arm gestures involved the mid upper arm (Figure 4c). **Practical implications:** (I₅) Design intermanual deictics centered in the specific target region on the support arm. This implication facilitates effective reaching and alignment with observed user preferences, such as taps in the palm or swipes in the mid of the forearm and upper arm, as shown in Figure 6. (I₆) Use the non-central areas for input that occurs less frequently or requires greater attention. For instance, a long tap or series of taps could be required on the outer edge of the upper arm to delete a file or confirm a purchase, where users are less likely to trigger it accidentally. Such a design also ensures that users are deliberate in their actions, minimizing the risk of unintended consequences.

④ **Expand the set of intermanual deictics with cross-region input.** The similarities observed in gesture characteristics across different arm regions suggest practical benefits of expanding input opportunities without considerable requirements for memorizing new gestures. **Supporting data:** The forearm and upper arm revealed the highest average coagreement rate (39.2%) across all ten referents considered in our study, and over 45.0% for a subset of five referents (Figure 8, right). **Practical implications:** (I₇) *Design gestures that begin in one region and end in another, i.e., cross-region deictics.* For example, a swipe that starts on the forearm and ends in the palm could mean advancing five items in a list, compared to a swipe solely on the forearm that advances one item at a time. This design allows different effects by reusing the same gesture across two connected arm regions. (I₈) *Design gestures performed sequentially across regions, such as starting on the forearm and repeating on the upper arm, i.e., sequential-region deictics.* Building on the previous example, if the forearm swipe is repeated, not continued, the result could be fast-forwarding to the end of the list.

⑤ **Favor designs of intermanual deictics that leverage users' prior experience with touchscreen devices.** The vast majority of the gestures elicited in our study were represented by touch and stroke input, indicating a legacy bias of how users interact with their personal devices. **Supporting data:** Across all regions, 91.2% of the gestures were either touches or strokes (Figure 3a). **Practical implications:** (I₉) *Design intermanual deictics that build on conventions from touchscreen input to increase the adoption of on-body interactions.* For example, use a double tap to open an app or a four-finger swipe to move between apps—two gestures reflective of interactions performed on prevalent digital devices.² (I₁₀) *Use the region on the support arm as a contextual element for touch input, associating it with the functionality of different digital devices.* For instance, the palm can be intuitively likened to a smartphone [19], while the forearm and upper arm can be conceptually associated with larger devices, such as remote controls, tablets, and displays [48]. Based on such associations, tapping the palm can initiate a phone call, swiping across the forearm might scroll through a list of movies, and using the upper arm to pinch can zoom in on a map shown on a remote display. Unlike Weigel et al. [70], who focused on the novelty of skin-specific gestures, and Lu et al. [41], who explored hand-to-hand gestures as a novel input modality compared to conventional touch input, we recommend capitalizing on users' familiarity with touchscreen devices as a transitional phase for shifting interactions from devices to the body.

⑥ **Design intermanual deictics that capitalize on users' preference for the index finger.** The index finger has several distinctive capabilities compared to the other fingers [30]: it is the most spatially acute finger of the hand, is used in many prehensile patterns, and, along with the thumb, is the most independent digit of the hand. Furthermore, prior work has shown that gesture input performed with the index finger is highly distinctive and easy to perform [10,56,61]. **Supporting data:** Our results revealed that the index finger was used in 94.3% of the elicited gestures, with 69.7% utilizing it exclusively (Figure 4d). **Practical implications:** (I₁₁) *Design intermanual deictics based on the perspective of the index finger.*

²Use multi-touch gestures on your Mac, <https://support.apple.com/en-us/102482>; Touch gestures for Windows, <https://support.microsoft.com/en-us/windows/touch-gestures-for-windows-a9d28305-4818-a5df-4e2b-e5590f850741>.

For example, this perspective can influence the choice of technology to sense gestures, e.g., using an electronic ring with motion sensing [15] vs. instrumenting the wrist [69] or arm [42]. (I₁₂) *Utilize interconnected abilities in humans that incorporate the index finger for more expressive interactions.* Since eye gaze is known to fixate near the index finger's contact point on grasped objects [9], we suggest applying existing design knowledge on combined touch+gaze input for conventional touchscreens [50] to explore opportunities in multimodal deictics. For example, tapping with the index finger on the opposite arm, observed repeatedly in our study across all regions (Figure 6), could activate a menu, while shifting gaze could select a specific menu item. Such designs open new opportunities for on-body interactions that leverage the referential abilities of multiple modalities, which we leave for exciting future work.

⑦ **Enhance the expressiveness of intermanual deictics by complementing index-finger-based input with design that incorporates other fingers.** To complement the previous guideline, we suggest designing intermanual deictics that leverage other fingers for parametrized input. **Supporting data:** We observed that some finger combinations occurred repeatedly in our study, such as the index and middle fingers occurring in 8.0% of the gestures, or input involving at least four fingers being observed in 10.8% of the elicited gestures (Figure 4d). **Practical implications:** (I₁₃) *Use additional fingers as parameters for input.* For example, a two-finger swipe with both the index and middle fingers could advance more quickly through a list of items compared to a swipe performed with just the index finger. (I₁₄) *Adopt design approaches from conventional touchscreen interactions that involve multiple fingers.* These may include the finger-count technique [3] or combined touch+hand pose input [38]. For instance, a three-finger tap in the palm could be used to directly select the third option in a menu, such as the third song in a playlist. The configuration of the other fingers could specify the intensity of an “increase” action, e.g., the fully stretched middle finger indicates a small increase, while spreading all the fingers apart signifies a larger increase.

⑧ **Complement contact-based with hover gestures performed in mid-air around the opposite arm.** According to our formalization of intermanual deictics in Section 3, these gestures do not require physical contact with the opposite arm, but can instead perform referential input from mid-air. Although none of these gestures made it into the consensus set (Figure 6), they highlight an interesting space for intermanual deictics where the support arm serves not as a touch surface, but as a pure point of reference. **Supporting data:** We found that 5.2% of the gestures elicited in our study were performed without making contact with the support arm (Figure 3a) with a notable preference in the forearm condition. **Practical implications:** (I₁₅) *Use the space around the opposite arm for novel interactions by adopting designs from around-device input.* These may include designs inspired by off-loading digital content around a mobile device [26] or implementing off-screen menus [54], adapted to the space around the opposite arm. In this context, we recommend aligning interactions with observed user preferences for the longitudinal (elbow to wrist) and transversal (ulnar to radial) axes. For example, tapping on the forearm could select a song in a music application, followed by a second tap at another location to play it, while the mid-air trajectory of the finger between the two taps—whether longitudinal or traversal,—could indicate “play

now” or “queue to play next.” (I₁₆) *Expand the set of intermanual deictics by duplicating physical-contact gestures in hover mode.* For example, a clockwise circular motion on the forearm could adjust the volume, increasing it incrementally, while the same motion above the forearm could switch between audio presets, such as “bass boost,” “vocal mode,” or “concert hall.”

7 Limitations

Our study has uncovered many insights into intermanual deictics, but it also presents limitations, which we address in the following. First, our findings are based on a set of ten generic referents only, whereas more particular referents, related to specific application areas—such as mobile computing (e.g., placing a call) [55], ambient intelligence (e.g., remote control of devices) [15], or mixed reality (e.g., summoning virtual objects) [51]—warrant further examination. This includes evaluating the suitability of intermanual deictics and the forms they might take in other contexts, beyond the seated position in our experiment, regarding type, scale, and complexity. Second, we did not address the recognition accuracy of intermanual deictics, as our goal was to explore gesture possibilities without imposing any technology-induced constraints on their articulation. Thus, the technical feasibility of implementing our gesture set using existing sensing and recognition technology remains to be verified. Third, our sample consisted mostly of males, with low female representation (19%). Although we did not intend to include this factor in our analysis, investigating potential sex differences in user preferences for intermanual deictics could be insightful, e.g., through a type-7 replication [17] involving the same method but new participants. To assist researchers in addressing these limitations and facilitate comparison with our findings, we provide our dataset at <http://www.eed.usv.ro/~vatavu>. Based on the most recent systematic review on gesture elicitation [64], this dataset—collected from 75 participants—represents the largest sample to date for on-body input. Next, we build on our insights into intermanual deictics to propose additional directions for future work.

8 Future Work

We envision promising future work on integrating intermanual deictics, as a distinctive class of gestures, into on-body interaction. We structure these opportunities around two main directions: enhancing wearable technologies to support intermanual deictics and exploring novel interactions that leverage their unique traits.

First, we believe that future explorations of intermanual deictics could also drive advances in engineering wearables to support their implementation. These may include new technology building on wrist-worn sensing [41], index-finger augmentation [61], radar systems [21], or computer vision [19,22] designed to enhance the body regions involved in intermanual deictics as well as new recognition algorithms tailored to their specific articulation. Such advancements would enable investigation of in-the-wild use cases with varying mobility conditions, such as running or cycling [63], limited upper-body mobility due to motor impairments [7], or encumbrance [46]—scenarios that may limit accessible regions on the support arm, thereby influencing the forms of intermanual deictics. Examining the accessibility of interactions integrating intermanual deictics represents interesting future work involving ability-based

design [72] in the specific context of on-body input. To this end, we recommend conducting comparisons between our gesture set and the on-body gestures preferred by users with various upper-body motor abilities [7] to facilitate interactions with computer systems. Furthermore, future work on sensing and recognition should examine use cases where gestures need to be detected through clothing [28], which may present challenges of lower sensing rates. This also includes addressing aspects of societal perception of interactions involving textile interfaces [52] as well as of interactions implemented with a device-augmented support arm [48].

Second, the specifics of intermanual deictics can inspire interaction techniques that leverage the intuitiveness of proprioception, the familiarity of pointing, and the dexterity of the index finger to expand current on-body input designs through meaningful gestures performed across various regions of the opposite arm or near it. Such interactions hold promise for applications in mixed reality that integrate virtual content with the user’s body, e.g., virtual objects attached to the forearm [24], placed near the open palm [2], or traversing across the user’s hands [71]. In this context, the location on the support arm could be used to summon different virtual objects, the choice of implementer could correspond to various manipulations of those objects, while the reference system of the support arm would anchor both the virtual content and the interaction, strengthening their connection and potentially enhancing perceived immersion and presence [66]. These design possibilities arise from leveraging the qualities of intermanual deictics—their bimanual structure, deictic nature, and asymmetric articulation—through the complementary roles of the support and implementer arms.

9 Conclusion

We reported empirical results on user preferences for intermanual deictics, a distinctive gesture class in the landscape of gesture-based interaction, characterized by a referential structure and asymmetrical postural-manipulative action. Our analysis unveiled user preferences for gestures that leverage the directional connotations in referents and exploit familiarity with touchscreen interactions, resulting in highly-consistent gesture input across the three regions we examined on the support arm. Based on these findings, we compiled a consensus set of intermanual deictics involving the palm, forearm, and upper arm, along with design principles and practical implications for interactive systems. Our contributions add to the existing body of knowledge for designing on-body interactions with insights from the largest-sample gesture elicitation study in this area. We look forward to innovations enabled by our findings and free dataset toward intuitive gesture-based input that effectively references the user’s body in novel interactive systems.

Acknowledgments

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References

- [1] Alexandru-Tudor Andrei, Laura-Bianca Bilius, and Radu-Daniel Vatavu. 2024. Take a Seat, Make a Gesture: Charting User Preferences for On-Chair and From-Chair Gesture Input. In *Proceedings of the CHI Conference on Human Factors in*

- Computing Systems (CHI '24)*. ACM, New York, NY, USA, Article 555, 17 pages. doi:10.1145/3613904.3642028
- [2] Takumi Azai, Mai Otsuki, Fumihisa Shibata, and Asako Kimura. 2018. Open Palm Menu: A Virtual Menu Placed in Front of the Palm. In *Proceedings of the 9th Augmented Human International Conference (AH '18)*. ACM, New York, NY, USA, Article 17, 5 pages. doi:10.1145/3174910.3174929
 - [3] Gilles Bailly, Eric Lecolinet, and Yves Guiard. 2010. Finger-Count & Radial-Stroke Shortcuts: 2 Techniques for Augmenting Linear Menus on Multi-Touch Surfaces. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 591–594. doi:10.1145/1753326.1753414
 - [4] Joanna Bergström and Kasper Hornbæk. 2019. Human-Computer Interaction on the Skin. *ACM Comput. Surv.* 52, 4, Article 77 (2019), 14 pages. doi:10.1145/3332166
 - [5] Joanna Bergstrom-Lehtovirta, Sebastian Boring, and Kasper Hornbæk. 2017. Placing and Recalling Virtual Items on the Skin. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 1497–1507. doi:10.1145/3025453.3026030
 - [6] Joanna Bergstrom-Lehtovirta, Kasper Hornbæk, and Sebastian Boring. 2018. It's a Wrap: Mapping On-Skin Input to Off-Skin Displays. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 564, 11 pages. doi:10.1145/3173574.3174138
 - [7] Laura-Bianca Bilius, Ovidiu-Ciprian Ungurean, and Radu-Daniel Vatavu. 2023. Understanding Wheelchair Users' Preferences for On-Body, In-Air, and On-Wheelchair Gestures. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, New York, NY, USA, Article 78, 16 pages. doi:10.1145/3544548.3580929
 - [8] İdil Bostan, Oğuz Turan Buruk, Mert Canat, Mustafa Ozan Tezcan, Cellalettin Yurdakul, Tilbe Gökşun, and Oğuzhan Özcan. 2017. Hands as a Controller: User Preferences for Hand Specific On-Skin Gestures. In *Proceedings of the 2017 Conference on Designing Interactive Systems (DIS '17)*. ACM, New York, NY, USA, 1123–1134. doi:10.1145/3064663.3064766
 - [9] Cristiana Cavina-Pratesi and Constanze Hesse. 2013. Why Do the Eyes Prefer the Index Finger? Simultaneous Recording of Eye and Hand Movements During Precision Grasping. *Journal of Vision* 13, 5 (2013), 15. doi:10.1167/13.5.15
 - [10] Edwin Chan, Teddy Seyed, Wolfgang Stuerzlinger, Xing-Dong Yang, and Frank Maurer. 2016. User Elicitation on Single-hand Microgestures. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, New York, NY, USA, 3403–3414. doi:10.1145/2858036.2858589
 - [11] Rune Haubo B. Christensen. 2022. ordinal—Regression Models for Ordinal Data. <https://CRAN.R-project.org/package=ordinal> version 2022.11-16.
 - [12] Rune Haubo Bojesen Christensen. 2023. Package 'ordinal'. Regression Models for Ordinal Data. <https://CRAN.R-project.org/package=ordinal>.
 - [13] Petru-Vasile Cioată and Radu-Daniel Vatavu. 2018. In Tandem: Exploring Interactive Opportunities for Dual Input and Output on Two Smartwatches. In *Companion Proceedings of the 23rd International Conference on Intelligent User Interfaces (IUI '18 Companion)*. ACM, New York, NY, USA, Article 60, 2 pages. doi:10.1145/3180308.3180369
 - [14] Nilofar Dezfūli, Mohammadreza Khalilbeigi, Jochen Huber, Florian Müller, and Max Mühlhäuser. 2012. PalmRC: Imaginary Palm-Based Remote Control for Eyes-Free Television Interaction. In *Proceedings of the 10th European Conference on Interactive TV and Video (EuroITV '12)*. ACM, New York, NY, USA, 27–34. doi:10.1145/2325616.2325623
 - [15] Bogdan-Florin Gheran, Jean Vanderdonck, and Radu-Daniel Vatavu. 2018. Gestures for Smart Rings: Empirical Results, Insights, and Design Implications. In *Proceedings of the 2018 Designing Interactive Systems Conference (DIS '18)*. ACM, New York, NY, USA, 623–635. doi:10.1145/3196709.3196741
 - [16] Bogdan-Florin Gheran, Radu-Daniel Vatavu, and Jean Vanderdonck. 2018. Ring x2: Designing Gestures for Smart Rings using Temporal Calculus. In *Proceedings of the ACM Conference Companion Publication on Designing Interactive Systems (DIS '18 Companion)*. ACM, New York, NY, USA, 117–122. doi:10.1145/3197391.3205422
 - [17] Bogdan-Florin Gheran, Santiago Villarreal-Narvaez, Radu-Daniel Vatavu, and Jean Vanderdonck. 2022. RepliGES and GESTory: Visual Tools for Systematizing and Consolidating Knowledge on User-Defined Gestures. In *Proceedings of the 2022 International Conference on Advanced Visual Interfaces (AVI '22)*. ACM, New York, NY, USA, Article 5, 9 pages. doi:10.1145/3531073.3531112
 - [18] Yves Guiard. 1987. Asymmetric Division of Labor in Human Skilled Bimanual Action: The Kinematic Chain as a Model. *Journal of Motor Behavior* 19, 4 (1987), 486–517. doi:10.1080/00222895.1987.10735426
 - [19] Sean Gustafson, Christian Holz, and Patrick Baudisch. 2011. Imaginary Phone: Learning Imaginary Interfaces by Transferring Spatial Memory from a Familiar Device. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology (UIST '11)*. ACM, New York, NY, USA, 283–292. doi:10.1145/2047196.2047233
 - [20] Sean G. Gustafson, Bernhard Rabe, and Patrick M. Baudisch. 2013. Understanding Palm-Based Imaginary Interfaces: The Role of Visual and Tactile Cues When Browsing. In *Proceedings of the CHI Conf. on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 889–898. doi:10.1145/2470654.2466114
 - [21] Ryo Hajjka, Tamil Selvan Gunasekaran, Chloe Dolma Si Ying Haigh, Yun Suen Pai, Eiji Hayashi, Jaime Lien, Danielle Lottridge, and Mark Billinghurst. 2024. RadarHand: A Wrist-Worn Radar for On-Skin Touch-Based Proprioceptive Gestures. *ACM Trans. Comput.-Hum. Interact.* 31, 2, Article 17 (jan 2024), 36 pages. doi:10.1145/3617365
 - [22] Chris Harrison, Hrvoje Benko, and Andrew D. Wilson. 2011. OmniTouch: Wearable Multitouch Interaction Everywhere. In *Proceedings of the 24th ACM Symposium on User Interface Software and Technology (UIST '11)*. ACM, New York, NY, USA, 441–450. doi:10.1145/2047196.2047255
 - [23] Chris Harrison and Haakon Faste. 2014. Implications of Location and Touch for On-Body Projected Interfaces. In *Proceedings of the 2014 Conference on Designing Interactive Systems (DIS '14)*. ACM, New York, NY, USA, 543–552. doi:10.1145/2598510.2598587
 - [24] Chris Harrison, Shilpa Ramamurthy, and Scott E. Hudson. 2012. On-Body Interaction: Armed and Dangerous. In *Proceedings of the Sixth International Conference on Tangible, Embedded and Embodied Interaction (TEI '12)*. ACM, New York, NY, USA, 69–76. doi:10.1145/2148131.2148148
 - [25] Chris Harrison, Desney Tan, and Dan Morris. 2010. Skininput: Appropriating the Body as an Input Surface. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 453–462. doi:10.1145/1753326.1753394
 - [26] Khalad Hasan, David Ahlström, and Pourang Irani. 2013. Ad-binning: Leveraging Around Device Space for Storing, Browsing and Retrieving Mobile Device Content. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 899–908. doi:10.1145/2470654.2466115
 - [27] Hayati Havlucu, Mehmet Yarkın Ergin, İdil Bostan, Oğuz Turan Buruk, Tilbe Gökşun, and Oğuzhan Özcan. 2017. It Made More Sense: Comparison of User-Elicited On-skin Touch and Freehand Gesture Sets. In *Distributed, Ambient and Pervasive Interactions*, Norbert Streitz and Panos Markopoulos (Eds.). Springer International Publishing, Cham, 159–171. doi:10.1007/978-3-319-58697-7_11
 - [28] Paul Holleis, Albrecht Schmidt, Susanna Paasoosaa, Arto Puikkonen, and Jonna Häkkinen. 2008. Evaluating Capacitive Touch Input on Clothes. In *Proceedings of the 10th International Conference on Human Computer Interaction with Mobile Devices and Services (MobileHCI '08)*. ACM, New York, NY, USA, 81–90. doi:10.1145/1409240.1409250
 - [29] Masoumehsadat Hosseini, Tjado Ihmels, Ziqian Chen, Marion Koelle, Heiko Müller, and Susanne Boll. 2023. Towards a Consensus Gesture Set: A Survey of Mid-Air Gestures in HCI for Maximized Agreement Across Domains. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, New York, NY, USA, Article 311, 24 pages. doi:10.1145/3544548.3581420
 - [30] Lynette A. Jones and Susan J. Lederman. 2006. *Human Hand Function*. Oxford University Press, NY, USA. doi:10.1093/acprof:oso/9780195173154.001.0001
 - [31] Shaun K. Kane, Jacob O. Wobbrock, and Richard E. Ladner. 2011. Usable Gestures for Blind People: Understanding Preference and Performance. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 413–422. doi:10.1145/1978942.1979001
 - [32] Maria Karam and m.c. schraefel. 2005. *A Taxonomy of Gestures in Human Computer Interactions*. Technical Report. University of Southampton. <http://eprints.soton.ac.uk/id/eprint/261149>
 - [33] Luv Kohli and Mary Whitton. 2005. The Haptic Hand: Providing User Interface Feedback with the Non-Dominant Hand in Virtual Environments. In *Proceedings of Graphics Interface 2005 (GI '05)*. Canadian HCCS, Waterloo, CAN, 1–8. <https://dl.acm.org/doi/10.5555/1089508.1089510>
 - [34] Panayiotis Koutsabasis and Panagiotis Vogiatzidakis. 2019. Empirical Research in Mid-Air Interaction: A Systematic Review. *Int. Journal of Human-Computer Interaction* 35, 18 (2019), 1747–1768. doi:10.1080/10447318.2019.1572352
 - [35] Christine Kühnel, Tilo Westermann, Fabian Hemmert, Sven Kratz, Alexander Müller, and Sebastian Möller. 2011. I'm home: Defining and evaluating a gesture set for smart-home control. *International Journal of Human-Computer Studies* 69, 11 (2011), 693–704. doi:10.1016/j.ijhcs.2011.04.005
 - [36] Gierad Laput, Robert Xiao, Xiang 'Anthony' Chen, Scott E. Hudson, and Chris Harrison. 2014. Skin Buttons: Cheap, Small, Low-Powered and Clickable Fixed-Icon Laser Projectors. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology (UIST '14)*. ACM, New York, NY, USA, 389–394. doi:10.1145/2642918.2647356
 - [37] Sang-Su Lee, Sohyun Kim, Bopil Jin, Eunji Choi, Boa Kim, Xu Jia, Daeop Kim, and Kun-pyo Lee. 2010. How Users Manipulate Deformable Displays as Input Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 1647–1656. doi:10.1145/1753326.1753572
 - [38] Hyunhul Lim, Jungmin Chung, Changhoon Oh, SoHyun Park, Joonhwan Lee, and Bongwon Suh. 2018. Touch+Finger: Extending Touch-based User Interface Capabilities with "Idle" Finger Gestures in the Air. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology (UIST '18)*. ACM, New York, NY, USA, 335–346. doi:10.1145/3242587.3242651
 - [39] Dekang Lin. 1998. An Information-Theoretic Definition of Similarity. In *Proceedings of the 15th International Conference on Machine Learning (ICML '98)*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 296–304. <https://dl.acm.org/doi/10.5555/645527.657297>
 - [40] Shu-Yang Lin, Chao-Huai Su, Kai-Yin Cheng, Rong-Hao Liang, Tzu-Hao Kuo, and Bing-Yu Chen. 2011. Pub - Point upon Body: Exploring Eyes-Free Interaction and

- Methods on an Arm. In *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology (UIST '11)*. ACM, New York, NY, USA, 481–488. doi:10.1145/2047196.2047259
- [41] Yiqin Lu, Bingjian Huang, Chun Yu, Guahong Liu, and Yuanchun Shi. 2020. Designing and Evaluating Hand-to-Hand Gestures with Dual Commodity Wrist-Worn Devices. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 4, 1, Article 20 (mar 2020), 27 pages. doi:10.1145/3380984
- [42] Yasutoshi Makino, Yuta Sugiura, Masa Ogata, and Masahiko Inami. 2013. Tangential Force Sensing System on Forearm. In *Proceedings of the 4th Augmented Human International Conference (AH '13)*. ACM, New York, NY, USA, 29–34. doi:10.1145/2459236.2459242
- [43] Denys J. C. Matthies, Simon T. Perrault, Bodo Urban, and Shengdong Zhao. 2015. Potential: Localizing On-Body Gestures by Measuring Electrical Signatures on the Human Skin. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM, New York, NY, USA, 207–216. doi:10.1145/2785830.2785859
- [44] David McNeill. 1992. *Hand and Mind: What Gestures Reveal About Thought*. University of Chicago Press, Chicago.
- [45] Florian Müller, Niloofar Dezfuli, Max Mühlhäuser, Martin Schmitz, and Mohamadreza Khalilbeigi. 2015. Palm-Based Interaction with Head-Mounted Displays. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '15)*. ACM, New York, NY, USA, 963–965. doi:10.1145/2786567.2794314
- [46] Alexander Ng, Stephen A. Brewster, and John H. Williamson. 2014. Investigating the Effects of Encumbrance on One- and Two- Handed Interactions with Mobile Devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, NY, USA, 1981–1990. doi:10.1145/2556288.2557312
- [47] Masa Ogata, Yuta Sugiura, Yasutoshi Makino, Masahiko Inami, and Michita Imai. 2013. SenSkin: Adapting Skin as a Soft Interface. In *Proceedings of the 26th ACM Symposium on User Interface Software and Technology (UIST '13)*. ACM, New York, NY, USA, 539–544. doi:10.1145/2501988.2502039
- [48] Simon Olberding, Kian Peen Yo, Suranga Nanayakkara, and Jurgen Steimle. 2013. AugmentedForearm: Exploring the Design Space of a Display-Enhanced Forearm. In *Proceedings of the 4th Augmented Human International Conference (AH '13)*. ACM, New York, NY, USA, 9–12. doi:10.1145/2459236.2459239
- [49] Marietta Papadatou-Pastou, Eleni Ntolka, Judith Schmitz, Maryanne Martin, Marcus R Munafò, Sebastian Ocklenburg, and Silvia Paracchini. 2020. Human Handedness: A Meta-Analysis. *Psychological Bulletin* 146, 6 (2020), 481–524. doi:10.1037/bul0000229
- [50] Ken Pfeuffer and Hans Gellersen. 2016. Gaze and Touch Interaction on Tablets. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology (UIST '16)*. ACM, NY, USA, 301–311. doi:10.1145/2984511.2984514
- [51] Thammathip Piumsomboon, Adrian Clark, Mark Billinghurst, and Andy Cockburn. 2013. User-Defined Gestures for Augmented Reality. In *CHI '13 Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. ACM, New York, NY, USA, 955–960. doi:10.1145/2468356.2468527
- [52] Halley P. Proffita, James Clawson, Scott Gilliland, Clint Zeagler, Thad Starner, Jim Budd, and Ellen Yi-Luen Do. 2013. Don't Mind Me Touching My Wrist: A Case Study of Interacting with on-Body Technology in Public. In *Proceedings of the 2013 International Symposium on Wearable Computers (ISWC '13)*. ACM, New York, NY, USA, 89–96. doi:10.1145/2493988.2494331
- [53] Francis Quek, David McNeill, Robert Bryll, Susan Duncan, Xin-Feng Ma, Cemil Kirbas, Karl E. McCullough, and Rashid Ansari. 2002. Multimodal Human Discourse: Gesture and Speech. *ACM Trans. Comput.-Hum. Interact.* 9, 3 (sep 2002), 171–193. doi:10.1145/568513.568514
- [54] Hanae Rateau, Yosra Rekkik, and Edward Lank. 2023. Ether-Mark: An Off-Screen Marking Menu For Mobile Devices. In *Proceedings of the 25th International Conference on Multimodal Interaction (ICMI '23)*. ACM, New York, NY, USA, 224–233. doi:10.1145/3577190.3614150
- [55] Jaime Ruiz, Yang Li, and Edward Lank. 2011. User-Defined Motion Gestures for Mobile Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, New York, NY, USA, 197–206. doi:10.1145/1978942.1978971
- [56] Adwait Sharma, Michael A. Hedderich, Divyanshu Bhardwaj, Bruno Fruchard, Jess McIntosh, Aditya Shekhar Nittala, Dietrich Klakow, Daniel Ashbrook, and Jürgen Steimle. 2021. SoloFinger: Robust Microgestures while Grasping Everyday Objects. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. ACM, New York, NY, USA, Article 744, 15 pages. doi:10.1145/3411764.3445197
- [57] Jürgen Steimle. 2016. Skin–The Next User Interface. *Computer* 49, 4 (apr 2016), 83–87. doi:10.1109/MC.2016.93
- [58] Jürgen Steimle, Joanna Bergstrom-Lehtovirta, Martin Weigel, Aditya Shekhar Nittala, Sebastian Boring, Alex Olwal, and Kasper Hornbæk. 2017. On-Skin Interaction Using Body Landmarks. *Computer* 50, 10 (oct 2017), 19–27. doi:10.1109/MC.2017.3641636
- [59] Radu-Daniel Vatavu. 2017. Smart-Pockets: Body-Deictic Gestures for Fast Access to Personal Data during Ambient Interactions. *International Journal of Human-Computer Studies* 103 (2017), 1–21. doi:10.1016/j.ijhcs.2017.01.005
- [60] Radu-Daniel Vatavu. 2019. The Dissimilarity-Consensus Approach to Agreement Analysis in Gesture Elicitation Studies. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, 13 pages. doi:10.1145/3290605.3300454
- [61] Radu-Daniel Vatavu. 2023. iFAD Gestures: Understanding Users' Gesture Input Performance with Index-Finger Augmentation Devices. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. ACM, New York, NY, USA, Article 576, 17 pages. doi:10.1145/3544548.3580928
- [62] Radu-Daniel Vatavu and Jacob O. Wobbrock. 2022. Clarifying Agreement Calculations and Analysis for End-User Elicitation Studies. *ACM Trans. Comput.-Hum. Interact.* 29, 1, Article 5 (jan 2022), 70 pages. doi:10.1145/3476101
- [63] Velko Vechev, Alexandru Dancu, Simon T. Perrault, Quentin Roy, Morten Fjeld, and Shengdong Zhao. 2018. Movespace: On-Body Athletic Interaction for Running and Cycling. In *Proceedings of the 2018 International Conference on Advanced Visual Interfaces (AVI '18)*. ACM, New York, NY, USA, Article 28, 9 pages. doi:10.1145/3206505.3206527
- [64] Santiago Villarreal-Narvaez, Arthur Sluÿters, Jean Vanderdonck, and Radu-Daniel Vatavu. 2024. Brave New GES World: A Systematic Literature Review of Gestures and Referents in Gesture Elicitation Studies. *ACM Comput. Surv.* 56, 5, Article 128 (2024), 55 pages. doi:10.1145/3636458
- [65] Santiago Villarreal-Narvaez, Jean Vanderdonck, Radu-Daniel Vatavu, and Jacob O. Wobbrock. 2020. A Systematic Review of Gesture Elicitation Studies: What Can We Learn from 216 Studies?. In *Proceedings of the 2020 ACM Designing Interactive Systems Conference (DIS '20)*. ACM, New York, NY, USA, 855–872. doi:10.1145/3357236.3395511
- [66] Ina Wagner, Wolfgang Broll, Giulio Jacucci, Kari Kuutti, Rod McCall, Ann Morrison, Dieter Schmalstieg, and Jean-Jacques Terrin. 2009. On the Role of Presence in Mixed Reality. *Presence: Teleoper. Virtual Environ.* 18, 4 (2009), 249–276. doi:10.1162/pres.18.4.249
- [67] Julie Wagner, Mathieu Nancel, Sean G. Gustafson, Stephane Huot, and Wendy E. Mackay. 2013. Body-Centric Design Space for Multi-Surface Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 1299–1308. doi:10.1145/2470654.2466170
- [68] Cheng-Yao Wang, Wei-Chen Chu, Po-Tsung Chiu, Min-Chieh Hsiu, Yih-Harn Chiang, and Mike Y. Chen. 2015. PalmType: Using Palms as Keyboards for Smart Glasses. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM, New York, NY, USA, 153–160. doi:10.1145/2785830.2785886
- [69] Cheng-Yao Wang, Min-Chieh Hsiu, Po-Tsung Chiu, Chiao-Hui Chang, Liwei Chan, Bing-Yu Chen, and Mike Y. Chen. 2015. PalmGesture: Using Palms as Gesture Interfaces for Eyes-Free Input. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM, New York, NY, USA, 217–226. doi:10.1145/2785830.2785885
- [70] Martin Weigel, Vikram Mehta, and Jürgen Steimle. 2014. More than Touch: Understanding How People Use Skin as an Input Surface for Mobile Computing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 179–188. doi:10.1145/2556288.2557239
- [71] Andrew D. Wilson and Hrvoje Benko. 2010. Combining Multiple Depth Cameras and Projectors for Interactions On, Above and Between Surfaces. In *Proceedings of the 23rd Annual ACM Symposium on User Interface Software and Technology (UIST '10)*. ACM, New York, NY, USA, 273–282. doi:10.1145/1866029.1866073
- [72] Jacob O. Wobbrock, Shaun K. Kane, Krzysztof Z. Gajos, Susumu Harada, and Jon Froehlich. 2011. Ability-Based Design: Concept, Principles and Examples. *ACM Trans. Access. Comput.* 3, 3, Article 9 (2011), 27 pages. doi:10.1145/1952383.1952384
- [73] Jacob O. Wobbrock, Meredith Ringel Morris, and Andrew D. Wilson. 2009. User-Defined Gestures for Surface Computing. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, New York, NY, USA, 1083–1092. doi:10.1145/1518701.1518866
- [74] Goshiro Yamamoto and Kosuke Sato. 2007. PALMbit: A Body Interface Utilizing Light Projection onto Palms. *The Journal of The Institute of Image Information and Television Engineers* 61, 6 (2007), 797–804. doi:10.3169/itej.61.797
- [75] Yang Zhang, Wolf Kienzle, Yanjun Ma, Shiu S. Ng, Hrvoje Benko, and Chris Harrison. 2019. ActiTouch: Robust Touch Detection for On-Skin AR/VR Interfaces. In *Proceedings of the 32nd Annual ACM Symposium on User Interface Software and Technology (UIST '19)*. ACM, New York, NY, USA, 1151–1159. doi:10.1145/3332165.3347869