# Take a Seat, Make a Gesture: Charting User Preferences for On-Chair and From-Chair Gesture Input

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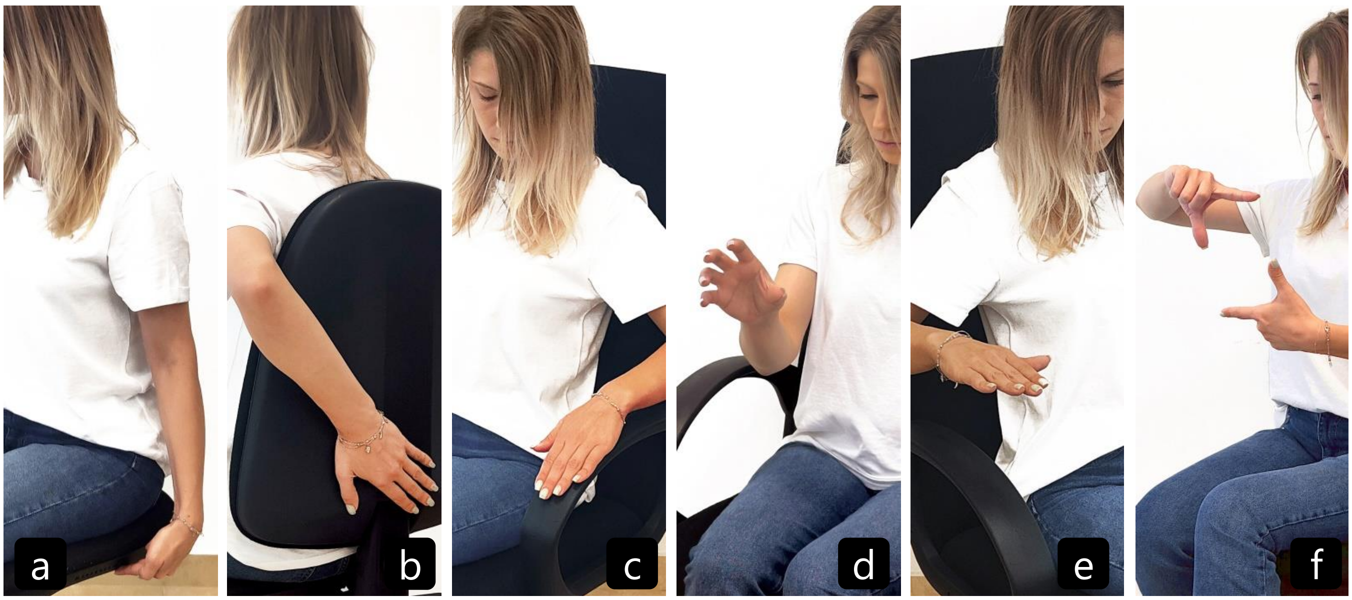


**Figure 1: We examine users' preferences for chair-based input of two distinct and complementary types: *on-chair* surface gestures performed on the chair's structural parts and *from-chair* mid-air gestures in the user's peripersonal space, around the chair. This figure showcases such "hand-chair gestures," highlighting variations in gesture type, extent, and number of hands.**

## ABSTRACT

We explore the chair as a referential frame for facilitating hand gesture input to control interactive systems. First, we conduct a Systematic Literature Review on the topic of interactions supported by chairs, and uncover little research on harnessing everyday chairs for input, limited to chair rotation and tilting movements. Subsequently, to understand end users' preferences for gestures performed on the chair's surface (i.e., *on-chair* gestures) and in the space around the chair (i.e., *from-chair* gestures), we conduct an elicitation study involving 54 participants, 3 widespread chair variations—armchair, office-chair, and stool,—and 15 referents encompassing common actions, digital content types, and navigation commands for interactive systems. Our findings reveal a preference for unimanual gestures implemented with strokes, hand poses, and touch input, with specific nuances and kinematic profiles according to the chair type. Based on our findings, we propose a range of implications for interactive systems leveraging *on-chair* and *from-chair* gestures.

## CCS CONCEPTS

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

## KEYWORDS

Gesture interaction, chairs, touch, surface gestures, mid-air gestures, gesture elicitation study

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# 1 INTRODUCTION

Chairs are an integral part of our daily lives as they support a significant portion of human activities, and numerous studies [57, 92, 110] have consistently reported that people spend an average of seven hours a day sitting. Whether it is the office chair at work, seats on buses, trains, or in waiting rooms, or the cozy armchair at home, a substantial portion of the day involves activities that require or benefit from some form of a chair. It is thus little surprise that chairs have also caught the attention of HCI researchers, who have leveraged their form factors for interactive systems. For example, the simple body movements of tilting or rotating a chair can be harnessed to control remote devices, from desktop computers [76, 77] and smartphones [90] to drones [40] and wall displays [18]. At the same time, a complementary line of work has focused on sensing users' body postures while seated to enhance work efficiency [58], bolster comfort and ergonomic support [63], promote driving safety [5], and facilitate social communication [70], respectively.

However, prior research on chairs for interactive systems has been limited to simple body movements and poses for tilting, rotating, rolling, or merely sitting in a chair [18, 40, 76, 77, 90], which constitute a limited interaction space compared to the richer possibilities offered by more expressive gesture modalities, such as touch [14], stroke-gesture [55], and mid-air [36] input. In fact, chairs offer a remarkably versatile input space, spanning from touch input on their structural parts, e.g., the armrest or the backseat, to hand movements performed around the chair, e.g., above the armrest or under the seat. In this space, the chair stands as a referential frame for gesture articulation. As we show in this paper, gesture input has been little examined in reference to chairs, yet it possesses distinctive nuances by being performed from a comfortable, seated position and leveraging the chair's form factor. Thus, we advocate for the importance of "hand-chair gestures," a unique blend of hands' dexterous movements and chairs' structural elements.

## 1.1 Hand-Chair Gestures

Hand-chair gestures are hand movements and poses performed in relation to the chair's structural parts or the seated position, which become the gesture support and reference. Following this operational definition, we make a key distinction between *on-chair* and *from-chair* gestures, each harnessing complementary aspects of the chair's potential for input, as follows.

- *On-chair gestures* utilize the chair's surface and structural elements, enabling touch, stroke, and grasp input, e.g., grasping the seat of a stool (Figure 1a), touching the backseat of an office-chair (Figure 1b), or swiping on the armrest of an armchair (Figure 1c) for fast and always-available tactile input to control an interactive system.
- *From-chair gestures* are non-contact, performed around the chair in the user's peripersonal space, e.g., turning a knob in mid-air with the elbow supported (Figure 1d), hovering a hand above the armrest (Figure 1e), or performing bimanual input while in the stable, seated position (Figure 1f).

While *on-chair* gestures transform the chair into an interactive surface, *from-chair* gestures extend the interactions beyond the chair's boundaries. Unfortunately, a systematic examination of such hand-chair gestures, where sitting in a chair enables a unique fusion of the user's highly dexterous hand movements and the chair's referential frame, has been lacking, despite the overall large interest in gesture input for interactive systems [36, 45, 55, 102].

## 1.2 Contributions

In this paper, we make the following contributions:

(1) We report results from a Systematic Literature Review (SLR) about interactions with computer systems supported by chairs for everyday users, and highlight limited research, primarily centered on tilting or rotating the chair.
(2) To understand user preferences and perceptions of hand-chair gestures, we conduct an end-user elicitation study involving 54 participants, 3 commonly encountered chair variations—the cozy *armchair*, the ergonomic *office-chair*, and the modest *stool*,—and 15 referents representing common actions, digital content types, and navigation commands for interactive systems. Our results highlight a preference for unimanual gestures involving strokes, poses, and touch input with specific kinematic profiles per chair type. We also report high perceived ease of use, recall, and social acceptability of hand-chair gestures.
(3) Based on our empirical findings, we propose actionable insights for integrating chairs as hand gesture sensing devices into interactive systems, represented by a set of six design implications, to unlock the potential of hand-chair gestures performed on and around the chair. Furthermore, to foster more work in this direction, we release our extensive dataset (1,620 numerical gestures with companion source code) freely available for research purposes.

# 2 CHAIRS IN INTERACTIVE SYSTEMS: A SYSTEMATIC LITERATURE REVIEW

A large body of literature exists on gesture interaction, including examinations of various gesture types [14, 45, 104], recognition techniques [14, 55, 91], and gesture set design methods [102, 109], to which we relate from the perspective offered by hand-chair gestures and the seated position. With respect to the latter, prior work has examined mid-air gestures designed to be used when in a relaxed state [74, 94, 100, 111]. For example, Zaiţi *et al.* [111] explored users' preferences for mid-air input during television watching, which they characterized as low-effort gestures for lean-back interaction. Veras *et al.*'s [100] mid-air spherical input space, where forearm angles are mapped to screen coordinates, fosters restful interaction from the couch: the arm rested, users are more likely to employ the forearm and wrist, not the whole arm, for restful mid-air elbow-anchored motion. Şiean *et al.* [86] explored locations in a living room where gesture sensing could be integrated for such restful input, among which the couch armrest and the coffee table for a sitting user. Additionally, when the user is sitting at a table, the surface of the tabletop affords even more ergonomic postures and resting opportunities for the arm and hand [11]. Such prior work, centered on the specific context of a user sitting, provides restful design alternatives to mid-air gesture-based interaction, specifically addressing movement fatigue [38].

Besides expert design, understanding users' preferences for intuitive and easy to use gesture commands has been primarily based on the gesture elicitation method [108]. For example, Vatavu [95] used the method to compare mid-air gestures with input using the TV remote control for home entertainment, and found that familiar point & click and drag & drop interaction models were preferred. By capitalizing on the gesture elicitation method, Jahani and Kavakli [37] proposed a variation based on descriptive mid-air gestures, while Lee *et al.* [48] combined elicitation with the Wizard-of-Oz approach to enable groups of two people, acting as performer and recognizer, to develop gestures through mutual conversation. We refer to Villarreal *et al.* [101, 102] for reviews of gesture elicitation studies and Hosseini *et al.* [36] for an analysis of mid-air gestures and a consensus gesture set compiled across different application domains.

In this rich literature of gesture-based interaction, chairs occur only sporadically and, when they do, rarely serve an interactive purpose. Nonetheless, prior work did examine interactions involving chairs, mostly represented by chair titling, rotation, and rolling [18, 40, 76, 77, 90]. To understand the extent of such contributions, we conducted a Systematic Literature Review (SLR) centered on interactions where the chair plays an active role; see next.

## 2.1 SLR Design and Implementation

We followed Siddaway *et al.*'s [85] SLR best practice guidelines to *identify*, *screen*, and confirm the *eligibility* of scientific contributions relevant to our scope of investigation, which we applied to bibliographic records available from the ACM Digital Library, the most comprehensive scientific database exclusively dedicated to computing,[1] and IEEE Xplore, the flagship digital platform for electrical engineering and computer science.[2] The following query,

```
"query": {Abstract: ((chair* OR armchair* OR stool*)
AND (interaction OR interface))}
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employing common chair type variations [17, 20, 80], yielded a total of 607 results in ACM DL and 296 in IEEE Xplore.[3] In the initial *screening* stage, we excluded a significant proportion (308/903=34.1%) of these results representing proceedings entries, which ended up in our list because of the use of the keyword "chair" with a different meaning than in our scope, e.g., Conference Chair. For the remaining entries, we applied the following eligibility criteria (EC):

- $EC_1$. *Peer-reviewed contributions only*. We exclusively focused on academic, peer-reviewed conference papers and journal articles. Additionally, we required that these papers be written in English and available in full text. Based on this criterion, we excluded 144 entries (15.9%), such as interviews [2], demo hours [62], keynote abstracts [25], session introductions [72], which featured the word "chair," but with other meanings.
- $EC_2$. *Specificity to seated users*. We excluded papers that did not involve seated users or where sitting in a chair was not at their core. For example, we excluded a multimodal interface for querying a database of 3D chair models [26] and a computer vision technique designed for segmenting the environment into object classes, including "floor," "chair," and "table" [93]. In total, 229 entries (25.4%) were excluded by this criterion.
- $EC_3$. *Specificity to standard chairs for general use*. Many results mentioned wheelchairs when discussing accessibility, even though their focus was not always the wheelchair itself. To maintain our emphasis on everyday chairs for general use, we excluded papers on instrumenting wheelchairs with technology [47, 71] and interactions for wheelchair users [8], since their scope was a specific user population. Furthermore, on-wheelchair gesture input has been explored before [4, 8, 56]. Following this criterion, a total number of 138 entries (15.3%) were excluded.
- $EC_4$. *Specificity to chair interaction*. Lastly, we excluded 56 contributions (6.2%) not portraying interactions between users and chairs or other systems, supported by chairs. These were papers where chairs were employed as measurement instruments [19] or papers that met all our previous criteria but did not address actual user interactions, e.g., Lee *et al.*'s [51] kinetic chairs that gradually become unstable to mediate intimate relationships between partners.

After the *eligibility* step, we arrived at 28 papers. Out of these, we excluded five [15, 21, 32, 43, 66] representing extensions or variations of the same works by the same authors [31, 42, 44, 60, 67]. Our final dataset comprised 23 papers published between 2006 and 2023, describing diverse interactive systems leveraging chairs. From these papers, we extracted information about input and output modalities, integrated technology, and user studies. Additionally, we utilized Wobbrock and Kientz's [107] categories of research contributions in HCI to categorize previous contributions in chair-based interaction. Two researchers independently extracted this information. The average Gwet's [29] AC1 coefficient was .900 (SD=.085) with a cumulative membership probability of 99.6% (SD=1.02%), indicating an almost perfect level of consensus according to the Landoch-Koch benchmarking scale [30]. The few discrepancies (accounting for 4.8% of the extracted information) were resolved via discussion and, when consensus could not be reached by the two coders, by majority vote with the intervention of a third researcher.

## 2.2 Results

Table 1 presents a summary of our findings. The most prevalent contribution type was *artifact,* present in all the papers, followed by *empirical research* (13/23=56.5%). Less commonly encountered contributions included methodological and theoretical ones, each present in five papers. The artifacts found many applications, from smartphones [90] to desktop computers [76, 77], large displays [18], drones [40], VR [31, 42, 44], entertainment [3, 33, 82, 84, 90], smart furniture [6, 28, 50, 67, 69], sedentary behavior interventions [60, 61, 65, 76, 87], user monitoring [22, 87], and care homes [3, 16, 61].

We found that a large percentage (56.5%) of the interactions featured in these papers centered around *armchairs*, followed by *office-chairs* (26.1%) and *stools* (21.7%). The most prevalent input modality was *body posture adjustment* (19/23=82.6%), exemplified by leaning [31, 40, 42, 44, 61], tilting [31, 40, 44, 61, 76, 77, 90], rocking [3, 65, 76, 77], or rotating [18, 22, 28, 31, 40, 42, 44, 65, 76, 77, 90] movements while seated. In contrast, touch [6, 84], mid-air [16, 22], pen [33], and hand-held [87] gestures, the norm for modern

[1] Noteworthy, the ACM Digital Library also includes references from other publishers, such as Springer-Verlag, Elsevier, MIT Press, among others, making it a comprehensive resource with over 700,000 records in the ACM Full-Text Collection; see details at https://dl.acm.org/about/content.

[2] Over 6 million records in electrical engineering and computers; https://ieeexplore.ieee.org/Xplorehelp/overview-of-ieee-xplore/about-ieee-xplore

[3] We ran the query on April 6, 2023 (ACM DL) and November 7, 2023 (IEEE Xplore).

**Table 1: Summary findings of our Systematic Literature Review on chair-based interaction.**

| Chair type [%]* | | Input modality | Output modality | Integrated technology† | Contribution type‡ | Gest.§ |
|---|---|---|---|---|---|---|
| Arm-chair | [56.5%] | body posture adjustments [3, 16, 18, 22, 31, 40, 60, 61, 69, 90], touch [6, 84], mid-air [16, 22], voice input [82] | visual [16], audio [3], haptic [22, 90], chair self-adjustments [6, 16, 60, 69] | sensing [3, 16, 18, 22, 40, 60, 61, 69, 82, 84, 90], actuation [6, 22, 60, 90], other [3, 6, 16, 31] | artifact (all), empirical [3, 6, 16, 18, 31, 61, 82, 90], methodological [6, 16, 31, 90], theoretical [82, 84] | 1-8 |
| Office chair | [26.1%] | body posture adjustments [42, 50, 65, 76, 77, 87], hand-held device [87] | visual [87], haptic [50], chair self-adjustments [50] | sensing [65, 76, 77, 87], actuation [50], other [42, 50, 87] | artifact (all), empirical [42, 65, 77], methodological [77], theoretical [50] | 1-7 |
| Stool | [21.7%] | body posture adjustments [28, 42, 44, 67], pen input [33] | visual [28, 33], chair self-adjustments [67] | sensing [28, 33, 67], actuation [67], other [28, 33, 42, 44] | artifact (all), empirical research [42, 44, 67], theoretical [33, 67] | 1-3 |

*Notes:* *One paper [42] featured both an office chair and a stool and, thus, the percentages in the Chair Type column, calculated out of a total of 23 papers, do not sum up to 100%. †*Sensing* technology included the Leap Motion controller, IMUs, pressure, ultrasonic, light, temperature, and MEMS sensors, and was used in 78.3% of the artifacts. *Actuation* technologies, including DC, servo, and stepper motors, were present in 26.1% of the artifacts. *Other* integrated technology included audio speakers, diffusive optical fibers, fiducial markers, robotic arms, and textile interfaces, present in 43.5% of the artifacts. ‡According to the categories in [107] specifying research contribution types in HCI. §The number of gestures used by the artifacts varied, e.g., the *armchair* interactive prototypes (first row) utilized between one and four gesture types.

interactive systems, were infrequently applied to chairs. Common output modalities were *chair self-adjustments* (26.1%), where the chairs changed shape or moved autonomously; see Table 1.

Our results also revealed that only thirteen of the papers examined in our SLR [3, 6, 16, 18, 31, 42, 44, 61, 65, 67, 77, 82, 90] conducted user studies, which involved between 2 and 30 participants (M=15.1, SD=7.4). For example, Brauner *et al.* [6] evaluated three touch-based interactions (touching the fold, bending the fold, and touching the stitches) performed with the index finger on a swatch of armchair fabric, and reported a positive user experience of controlling the armchair. Endert *et al.* [18] conducted an evaluation of chair rotation to facilitate cursor movements on a large display, a technique designed to complement conventional mouse input. The findings showed that users significantly reduced their mouse movements and positively changed the way of accomplishing the interactive task. Merilampi *et al.* [61] examined sedentary behavior in the context of a smart chair prototype, which required users to stand up and move to control a video game, e.g., stand up, jump, and sit back on the chair. Other studies took a more informal approach to evaluate chair interactions. For instance, Oozu *et al.*'s [67] "Escaping Chair," a stool designed to interact with bystanders by moving away from them, underwent evaluation during an exhibition event. Visitors, after interacting with the stool, reported a sense of personified intentions in the chair and expressed sympathy toward it. Overall, chair interactions evaluated in the scientific literature have employed a limited range of gestures, from as few as one [18, 50, 60, 67, 69, 82, 84] to as many as eight [31] (Mdn=3, M=2.9, SD=2.1).

## 2.3 Summary

Our findings revealed that interactions with computer systems involving the chair as a key element have been limited in both number and scope. These interactions have primarily focused on *body posture adjustments,* e.g., for chair tilting and rotation-based input, and leveraged *chair self-adjustments* in response. Thus, the prospective interaction possibilities offered by the chair as a referential frame for more dexterous, expressive, socially acceptable, and restful hand gestures, in contrast to whole-body pose adjustments while seated, remain largely untapped. In particular, *on-chair* gestures, which transform the chair's structural elements into interactive surfaces for input, and *from-chair* gestures, which extend the interactions beyond the chair's physical boundaries, have received little attention. To understand users' preferences for such hand-chair gesture input, we conducted an end-user gesture elicitation study; see next.

# 3 STUDY

We conducted a study to obtain insights into users' preferences of hand-chair gesture input implemented with *on-chair* and *from-chair* gestures. To this end, we utilized the end-user elicitation method [99, 106, 108] with a mixed experiment design involving three commonly encountered chair variations [17, 20], i.e., *stool*, *office-chair*, and *armchair*.

## 3.1 Participants

Fifty-four people (45 self-identified as male and 9 as female), aged between 18 and 44 years old (M=23.3, SD=5.6), participated in our study following recruitment via a technical university mailing list and convenience sampling. Participants reported regular use of smartphones and laptops and an average daily sitting time of 7.5 hours (SD=2.2)—a significant portion of their day and in line with the average sitting time, of approximately 7 hours per day, consistently reported in large studies [57, 92, 110]. We randomly assigned participants to one of three groups in our study—corresponding to *stool*, *office-chair*, and *armchair*,—with identical male-female ratios

**Table 2: The list of referents used in our end-user elicitation study about hand-chair gesture input.**

| | | Referent† | Description of the referents provided to the participants | References |
|---|---|---|---|---|
| Actions | 1. | Place/answer call | Answer/end an incoming phone call | [23, 79] |
| | 2. | Set/cancel alarm | Activate/deactivate the most recent alarm (the alarm is set if off and vice versa) | [23] |
| | 3. | Turn on/off lights | Turn on/off the lights (lights turn on if they are off and vice versa) | [23, 41] |
| | 4. | Turn on/off TV | Turn on/off the TV (the TV turns on if it is off and vice versa) | [23, 41] |
| | 5. | Turn on/off AC | Turn on/off the air conditioner (the air conditioner turns on if off and vice versa) | [23] |
| Content | 6. | Photos and videos | Get direct access to photos/videos; the first photo is displayed on a screen | [41, 83] |
| | 7. | Music | Get direct access to music; the first file starts playing | [23, 83] |
| | 8. | Messages | Get direct access to messages; the most recent message is displayed on a screen | [39, 41] |
| | 9. | Agenda/calendar | Get direct access to the agenda/calendar, displayed on a screen | [83] |
| | 10. | Contacts | Get direct access to phone contacts, which are displayed on a screen | [79] |
| Navigation | 11. | Next | Go to the next element in a list, e.g., show next photo, go to next TV channel | [23, 39, 41, 49, 73, 77, 79, 108] |
| | 12. | Previous | Go to the previous element in a list, e.g., previous photo, previous TV channel | [23, 39, 41, 49, 73, 77, 79, 108] |
| | 13. | Increase | Increase the value of a parameter, e.g., audio volume, light intensity, etc. | [23, 39, 41, 64, 73, 77, 79] |
| | 14. | Decrease | Decrease the value of a parameter, e.g., audio volume, light intensity, etc. | [23, 39, 41, 64, 73, 77, 79] |
| | 15. | Home screen | Go to the home screen of the current application | [49, 64, 77, 79] |

†While the names of the referents (first column) may vary across various studies, our primary consideration was their intended effect.

(45/3=15 male and 9/3=3 female per group). Kruskal-Wallis tests revealed our groups well balanced in terms of age ($\chi^2_{(2)}$=0.624, $p$=.732, *n.s.*) and daily sitting time ($\chi^2_{(2)}$=2.282, $p$=.320, *n.s.*). Seven of the participants self-reported as left-handed and 38 as right-handed.

## 3.2 Procedure

According to the end-user elicitation method [108], we collected gestures in relation to specific referents, e.g., answer an incoming phone call or access photos. To encompass a diversity of system functions, we employed 15 commonly used referents from previous gesture elicitation studies, which we presented on paper with short descriptions. We selected our referents to be representative of (i) common system actions, e.g., turning on/off various devices, (ii) accessing digital content, e.g., music or photos, and (iii) performing generic navigation in interactive systems, e.g., next/previous, home screen; see Table 2. To arrive at these referents, we relied on the top-10 most influential gesture elicitation studies, according to Villarreal *et al.*'s [102, p. 860] systematic literature review as well as elicitation studies focused on digital content type [83], chair-based interaction [77], and finger instrumentation for gesture input [23].

Participants signed a consent form and filled out a demographic questionnaire. Subsequently, they received the following instructions: "For the following list of referents, propose hand gestures on the chair and in air from the seated position. Your gestures should be easy to execute and recall, a good fit to the referents, and acceptable in a public place. You are free to use either hand or both hands to perform the gestures." After confirming they understood the task, participants were given as much time as needed to come up with suitable gestures. Subsequently, one *on-chair* and one *from-chair* gesture were recorded for each referent using a video camera and two TapStrap v2 finger-augmentation devices (featuring a 3-axis accelerometer per finger, Bluetooth 4.0, low weight of just 200g) [88] worn on both hands. Our custom Android software application stored the gestures as series of 3D linear acceleration points for the ten fingers. The order of referents was randomized per participant, while gesture locale, *on-chair* and *from-chair*, was randomized per referent. Participants were not allowed to use the same gesture for multiple referents within the same gesture locale, but were allowed to reuse the gesture for the same referent across gesture locales, e.g., "letter M" drawn in mid-air or on the chair's seat for "Music."

## 3.3 Design and Measures

Our study was a mixed design with one between-subjects variable, ChairType (nominal with three conditions, *stool*, *office-chair*, and *armchair*), and one within-subjects variable, GestureLocale (nominal with two conditions, *on-chair* and *from-chair*). The ChairType conditions cover common chair variations [17, 20, 80] with increasingly more complex form factors and, thus, richer possibilities for hand-chair gesture input. Although the referents specify the conditions of another within-subjects variable, Referent, we are not interested in this effect, since we see the referents as one sample drawn from all possible system functions. Consequently, we perform data aggregation on this variable or modeled it as a random effect, according to the statistical model; see Subsection 3.4. The dependent variables are the measures used to characterize our participants' gesture articulations and preferences, as follows.

### 3.3.1 *Measures of gesture articulation.*

We utilized the video recordings to extract the following information:

- Handedness indicates the hand(s) employed to articulate the gesture. Following McNeill [59], we used four categories: *left hand (LH)*, *right hand (RH)*, *two same hands (2SH)*, and *two different hands (2DH)*.[4] Bimanual gestures, 2SH and 2DH, specify whether both hands act synchronously, perform the

[4]Terminology and abbreviations used by McNeill [59, p. 379] for gesture coding, which we adopt exactly for consistency purposes.

same movement, and form the same pose during gesture articulation, i.e., they are the same (2SH) or different (2DH).

- GestureType with six categories, adopted from [4]: *pointing* (the hand points in mid-air or to a specific chair part), *touch input* (a tap or variation of a tap on the chair), *grasp* (the hand firmly grasps a part of the chair), *stroke-gesture* (the hand swipes or draws symbols on the chair's surface or in mid-air), *hand pose* (the hand forms a symbolic pose, such as "thumbs-down," or mimics a manipulative pose, e.g., knob turning), and *mixed* (any combination of the previous categories, e.g., draw a letter and subsequently tap twice on the armrest). These categories expand Wobbrock *et al.*'s [108] "form" dimension to both surface and mid-air gesture input.
- GestureExtent delineates the physical reach of the gesture. We characterize the extent of *on-chair* gestures with the chair part they involve by considering three regions—*armrests, seat,* and *backrest,*—corresponding to the principal structural elements of seating design [68]. We characterize the extent of *from-chair* gestures with McNeill's [59, p. 378] "gesture space," a division of concentric squares of the space around a person while seated, with three regions—*center*, *periphery*, and *extreme-periphery*;[5] see Figure 3, top.

Two researchers independently extracted this information from the video recordings following a two-stage process. In the initial stage, both researchers coded the same videos, representing a random subset of twelve participants (22.2% of the data), which yielded an average Gwet's [29] AC1 coefficient of .888 (SD=.097) and a cumulative membership probability of 99.997% (SD=0.01%), indicating an almost perfect level of consensus according to the Landoch-Koch benchmarking scale [30]. The few discrepancies (8.24% of the extracted information) were resolved through discussion and, when consensus could not be reached by the two coders, by a majority vote with the intervention of a third researcher. In the second stage, each of the two researchers coded half of the remaining videos.

We also used the numerical gesture representations provided by the TapStrap finger-augmentation devices to automatically compute other measures of gesture articulation. Each gesture was represented as a set of linear accelerations for each of the ten fingers, $g = \{a_{i,j}=(x_{i,j}, y_{i,j}, z_{i,j}, t_i) \mid i=1..n, j=1..10\}$, where $j$ specifies the finger and $n$ is the number of points on the gesture path. During a preprocessing stage, we removed the influence of the force of gravity with a high-pass filter [27], left-trimmed the gestures by 300ms (a systematic bias that we observed in the data between the participants' and experimenter's synchronization during gesture recording), and resampled at 100Hz. Data preprocessing steps such as these are common for accelerated motion [46, 54, 97]. Subsequently, we computed the following measures:

- ProductionTime, expressed in milliseconds, a pivotal factor in assessing gesture input performance [7, 52].
- NumAxesMovement, dimensionless, represents the number of axes on which acceleration is detected, adapted from Ruiz *et al.*'s [79] "dimension" category of their taxonomy of user-elicited motion gestures. We counted the number of axes for which the MeanAcceleration exceeded 0.1g, a threshold adopted from [35, 98].
- MeanAcceleration, reports the average magnitude, in m/s$^2$, of the linear acceleration of the hands' movement during gesture articulation. Adopted from [34, 78, 97], we adapted the measure to compute for ten fingers:

$$\text{MeanAcceleration}(g) = \frac{1}{10n}\sum_{j=1}^{10}\sum_{i=1}^{n}(x_{i,j}^2 + y_{i,j}^2 + z_{i,j}^2)^{\frac{1}{2}} \quad (1)$$

Eq. 1 computes a numerical value of the average acceleration magnitude across all the sampled points $i$ on the gesture paths of each finger $j$=1..10. This measure, in its simplified form involving just one moving object (finger/hand), has also been referred to in the scientific literature as gesture strength [34] or energy [78].

*3.3.2 Measures of gesture similarity and consensus.* To understand participants' level of consensus over suitable hand-chair gestures for the referents used in our study, we adopted the *computer analysis model,* recommended in Vatavu and Wobbrock [99], implemented with the dissimilarity-consensus approach [96]. According to this approach, the relationship between participants' consensus ($C$) over their gesture articulations and the tolerance ($\tau$) under which two gestures are considered equivalent, given a dissimilarity measure ($\delta$), is modeled with logistic functions:

$$C(\tau) = \frac{C_\infty \cdot C_0}{C_0 + (C_\infty - C_0)\cdot \exp(-r\cdot\tau)} \quad (2)$$

where $C_\infty = \lim_{\tau\to\infty} C(\tau)$ and $C_0 = \lim_{\tau\to 0} C(\tau)$ are the upper and lower bounds of consensus and $r$ is the growth rate. Following recommendations in [96], we implemented $\delta$ with Dynamic Time Warping (DTW), a robust and versatile approach to gesture recognition [89]. Larger $r$ values indicate faster reaching consensus [96].

*3.3.3 Measures of gesture preference.* We collected participants' perceptions of their gestures via 7-point Likert scales:

- Ease, adopted from Wobbrock *et al.* [108], measures the perceived ease of gesture articulation, in response to the statement "The gesture I picked is easy to perform," from 1 (strongly disagree) to 7 (strongly agree).
- Goodness, adopted from Wobbrock *et al.* [108], measures the goodness of fit between the proposed gesture and the corresponding referent, in response to "The gesture I picked is a good match for its intended purpose."
- Recall, adapted from Zaiţi *et al.* [111], measures user perception of the recall likeliness of the proposed gesture through the level of agreement with the statement "The gesture I picked is easy to recall."
- SocialAcceptability, adapted from Rico and Brewster [78], measures the participant's willingness to perform the proposed gesture in public, as a reaction to the statement "I am willing to perform this gesture in public."

[5] To maintain coding simplicity, we treated McNeill's [59] "center-center" as part of the "center" region, similar to previous work [4]. For gestures spanning multiple regions, we considered the largest region encompassing the gesture. For example, a swipe gesture performed upwards, starting in the *center* in front of the body, traversing the *periphery*, and ending in the *extreme-periphery* above the user's head, was coded as an *extreme-periphery* gesture.

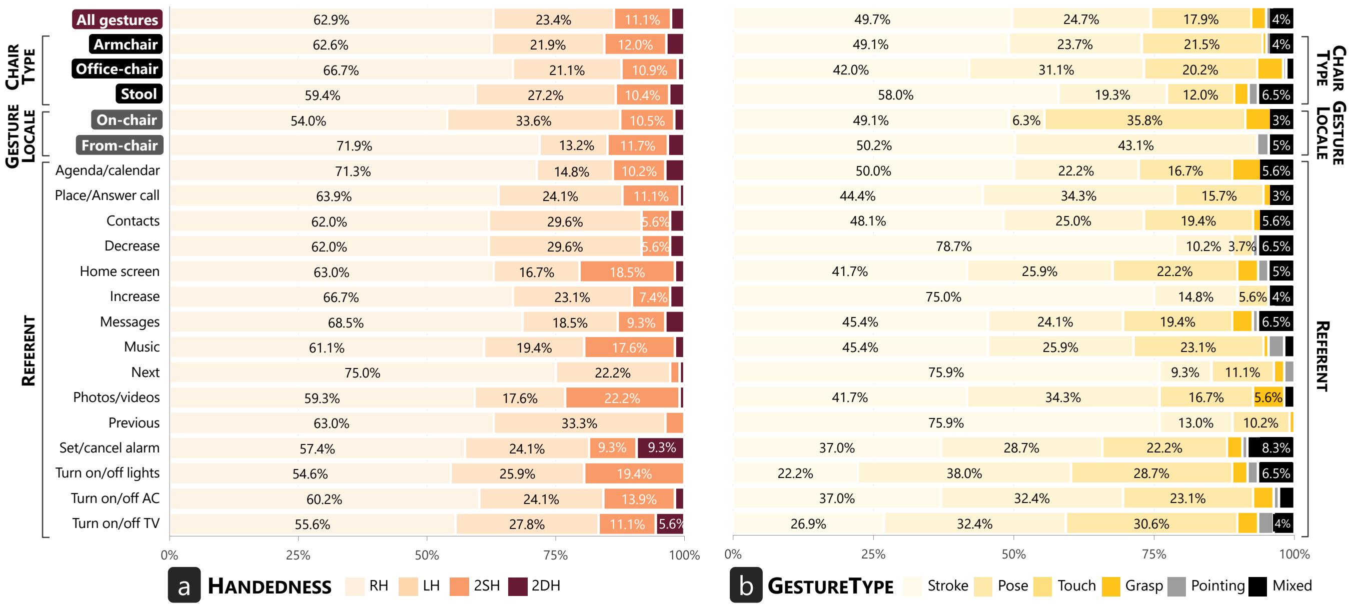


**Figure 2: Distribution of Handedness and GestureType for the elicited gestures. Note the large proportion of *unimanual* vs. *bimanual* gestures (left chart) and *stroke-gestures, hand poses,* and *touch input* compared to other gesture types (right).**

## 3.4 Statistical Analysis

To analyze categorical and ordinal variables with polytomous responses in our mixed design, e.g., Handedness or GestureType, we employed Cumulative Link Mixed Models [12] with maximum likelihood estimates of the parameters provided by the Laplace approximation method [13] with participants nested within ChairType, and Referent treated as a random effect. To assess the statistical significance of specific model terms, e.g., the effect of ChairType, we used likelihood-ratio chi-squared tests for pairs of models of progressive complexities. Additionally, we applied mixed ANOVA for the measures automatically computed from numerical gesture descriptions, e.g., MeanAcceleration. For $\tau - C$ analysis of consensus rates, we employ logistic modeling [96].

# 4 RESULTS

We present results from an analysis of 1,620 hand-chair gestures (=54 participants × 2 gesture locales × 15 referents), for which we extracted a total of 9,720 articulation characteristics, computed 6,885 dissimilarity measurements, and collected 6,480 self-reported gesture ratings. In total, we report empirical findings based on a dataset of 23,085 records.

## 4.1 Gesture Articulation Characteristics

*4.1.1 Handedness.* The large majority of the gestures (86.3%) was unimanual (62.9% RH and 23.4% LH), whereas bimanual articulations were characterized by symmetry (11.1% vs. 2.6% for 2SH and 2DH, respectively); see Figure 2a. This distribution remained consistent across ChairType, with no significant effect on Handedness ($\chi^2_{(2)}$=1.289, $p$=.525, *n.s.*). The proportion of unimanual and bimanual gestures also remained consistent across *on-chair* and *from-chair* gestures (87.6% and 85.1%), but with notable differences within each category, according to a significant effect of GestureLocale ($\chi^2_{(1)}$=98.677, $p$<.001) confirmed by post-hoc tests (FDR $p$-value adjustments applied) for each chair type ($p$<.05). For instance, we observed a stronger preference for RH over LH *from-chair* gestures (71.9% vs. 13.2%), but less pronounced for *on-chair* (54.0% vs. 33.6%)—a finding revealing that the chair surface encouraged a more balanced use of both hands for gesture articulation compared to the open space around the user.

By following up on a significant ChairType × GestureLocale interaction ($\chi^2_{(2)}$=13.656, $p$<.005), we noted differences between the Handedness distributions of *armchair* × *from-chair* and *stool* × *on-chair* ($p$=.004), *office-chair* × *from-chair* and *stool* × *on-chair* ($p$=.005), and *armchair* × *on-chair* and *stool* × *from-chair* ($p$=.049) gestures. The common factor behind these differences was the *stool*'s well-balanced distribution of LH and RH *on-chair* gestures (45.6% and 41.9%), which can be attributed to the increased importance of hand choice in differentiating among gestures to compensate for the *stool*'s smallest surface area across all chair types. Noteworthy, different Handedness distributions were observed across the specific referents that we examined; see Figure 2a, bottom. For example, "Next" and "Previous" predominantly favored unimanual gestures (97.2% and 96.3%), while other referents, such as "Photos and videos" and "Home screen," exhibited the largest percentage of bimanual gestures (23.1% and 20.4%). Out of these, symmetrical *from-chair* gestures included clapping, swiping, and extending the arms with synchronized movements, while asymmetrical ones primarily involved using one hand as support for writing or drawing with the other. Bimanual *on-chair* gestures included touching, swiping, or grasping various chair parts.

We also found that participants' handedness transpired into their gesture articulations. On average, left-handed participants exhibited an equal percentage of LH and RH gestures (37.1%), whereas right-handed ones predominantly performed RH (67.3%) than LH (21.3%) gestures. Additionally, left-handed participants engaged in bimanual gestures twice as frequently (25.7%) as their right-handed counterparts (11.9%). These findings were confirmed by significant Kendall correlations between self-reported handedness (binary coded, where 0 denotes left-handedness and 1 denotes right-handedness) and participant preference for RH ($\tau_{(54)}$=.287, $p$=.013) and bimanual gestures ($\tau_{(54)}$=−.319, $p$=.007), respectively.

*4.1.2 Gesture type.* We found that *stroke-gestures* were overall preferred by our participants (49.7%), followed by *hand poses* (24.7%) and *touch input* (17.9%), whereas the other gesture categories—*grasp*, *pointing*, and *mixed*,—were considerably less represented, accounting for just 7.7% in total; see Figure 2b. We did not detect a statistically significant effect of ChairType on GestureType ($\chi^2_{(2)}$=2.774, $p$=.250, *n.s.*), but we observed a significant effect of GestureLocale ($\chi^2_{(1)}$=397.604, $p$<.001), reinforced by post-hoc tests (with FDR $p$-value adjustments) across all chair types. The large majority of *from-chair* gestures consisted of *stroke-gestures* and *hand poses* (93.3%), while *on-chair* gestures were primarily composed of *stroke-gestures*, *hand poses*, and *touch input* (91.2%). Notably, *from-chair* articulations favored considerably more *hand poses* (43.1% vs. 6.3%), whereas *touch input* and *grasps* were used in the *on-chair* condition (35.8% and 5.3%, respectively).

*Stroke-gestures*, *hand poses*, and *touch input*, in that order, were the most preferred gesture types across all chair types, yet with nuances revealed by a significant ChairType × GestureLocale interaction ($\chi^2_{(2)}$=32.495, $p$<.001) with post-hoc tests confirming significant differences (FDR-adjusted $p$<.001) across all 3×2 pairs. For example, the *stool* exhibited the lowest percentage of *touch input* usage (12.0%) in favor of the highest percentage of *stroke-gestures* (58.0%) compared to the *office-chair* (20.2% and 42.0%) and *armchair* (21.5% and 49.1%). Participants also proposed more *grasp* gestures for *stool* and *office-chair* (2.6% and 4.6%) than in the case of the more expansive *armchair* (0.7%). Figure 2b, bottom reports the observed GestureType distributions per referent. Referents with directional connotations, such as "Next," "Previous," "Increase," and "Decrease," had the highest percentage of *stroke-gestures* (ranging from 75.0% to 78.7%), whereas referents that mimicked actions typically performed with remote controls, such as "Turn on/off lights," "Turn on/off AC," and "Turn on/off TV," favored the highest percentages of *hand pose* (32.4% to 38.0%) and *touch input* (23.1% to 30.6%). Additional insights into the spatial regions encompassing these gesture types are presented next.

*4.1.3 Gesture extent.* Figure 3, top presents the spatial regions where *on-chair* and *from-chair* gestures were performed, according to ChairType. The majority of *from-chair* gestures were encompassed by the *periphery* (45.8%) and *extreme-periphery* (42.8%) of the user's peripersonal space, while only a small portion (11.4%) was observed in the *center*, with no significant effect of ChairType on *from-chair* GestureExtent ($\chi^2_{(2)}$=0.862, $p$=.650). The effect was, however, statistically significant for the *on-chair* gestures ($\chi^2_{(2)}$=14.033, $p$<.001), most of which being associated with the seat (70.6%), with articulations performed either on the seat's surface (35.2%) or underneath it (35.4%). Our findings show that the armrests, when available, were preferred as the most convenient and easily accessible surface for input, e.g., 73.3% of the *armchair* gestures involved them. When the armrests were absent, participants harnessed other distinctive chair parts, e.g., 10.4% of the *office-chair* gestures were performed on the backrest vs. just 4.5% for the *armchair*. The *stool*, lacking both armrests and a backrest and featuring limited surface area, led to *on-chair* gestures that exclusively used the seat. Among these, 57.8% were underneath the seat, including the seat sides and corners.

Figure 3, bottom provides a visual summary of the relationships among GestureExtent, Handedness, and GestureType for each ChairType. Each circular chart highlights the percentage of gestures within specific pairs of gesture categories, e.g., the RH category of Handedness and the armrest category of GestureExtent. To this end, the charts employ ribbons whose widths are proportional to the respective percentages, offering a breakdown of the overall GestureExtent percentages depicted in Figure 3, top. For example, in the *armchair*, *office-chair*, and *stool* conditions, 2SH gestures represented 6.7%, 9.5%, and 10.0% of the seat-referenced gestures, a series of values that align with the increasing trend of seat gesture percentages from Figure 3, top. Similarly, *stroke-gestures* accounted for 65.1%, 68.5%, and 73.7% of all the articulations performed in the *extreme-periphery*, following the increasing trend observed for that region. These findings reveal consistent participant preferences regarding the number of hands and gesture type at various locations on and around the chair, respectively. Next, we continue our analysis by examining gesture kinematic profiles.

## 4.2 Kinematic profiles of gesture articulation

On average, hand-chair gestures were produced in 2.4s in the *armchair*, 2.5s in the *office-chair*, and 2.6s in the *stool* condition, with no significant effect of ChairType ($F_{(2,51)}$=0.262, $p$=.771, *n.s.*); see Figure 4a. However, we found a significant effect of GestureLocale ($F_{(1,51)}$=34.288, $p$<.001) and a ChairType × GestureLocale interaction ($F_{(2,51)}$=3.596, $p$=.035). *From-chair* gestures were about 10% faster than *on-chair* ones (2.4s vs. 2.6s), with the largest difference in ProductionTime observed for *armchair* (11.5%) and *stool* (11.3%) compared to just 3.2% for *office-chair* (2.4s vs. 2.5s). We also found that the elicited gestures required at least two axes of movement, with no significant effect of ChairType ($F_{(2,51)}$=0.246, $p$=.783, *n.s.*), but a significant effect of GestureLocale ($F_{(1,51)}$=32.633, $p$<.001), revealing more expansive *from-chair* gestures (2.3 vs. 1.9); see Figure 4b. Lastly, the mean acceleration of the elicited gestures varied between 2.8m/s$^2$ for *armchair* and 3.4m/s$^2$ for *stool*, but with no significant effect of ChairType ($F_{(2,51)}$=1.197, $p$=.310, *n.s.*). However, *from-chair* articulations required significantly more acceleration compared to *on-chair* ones (3.5m/s$^2$ vs. 2.7m/s$^2$, $F_{(1,51)}$=73.650, $p$<.001), accounting for a difference of 30%; see Figure 4c.

## 4.3 Gesture Ratings

Figure 5 presents participants' self-ratings of their gestures, which consistently trended towards high scores, i.e., 93.6% of the Goodness ratings fell above the midpoint item of the rating scale, and similarly for Ease (98.5%), Recall (96.9%), and SocialAcceptability

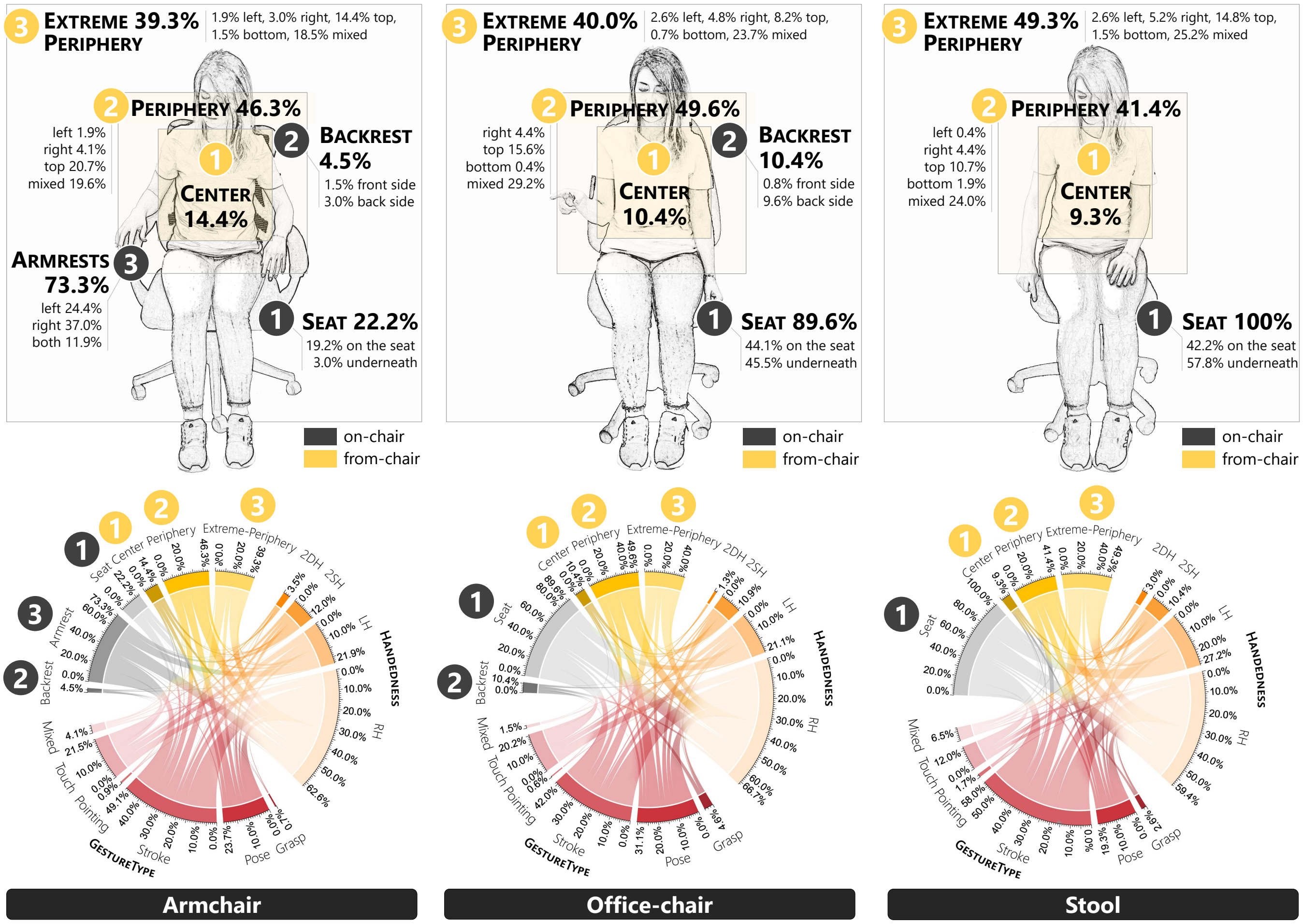


**Figure 3: Top: distribution of GestureExtent for the elicited *on-chair* and *from-chair* gestures for each ChairType. Bottom: relationships observed between GestureExtent with Handedness and GestureType; also refer to Figure 2 for the latter.**

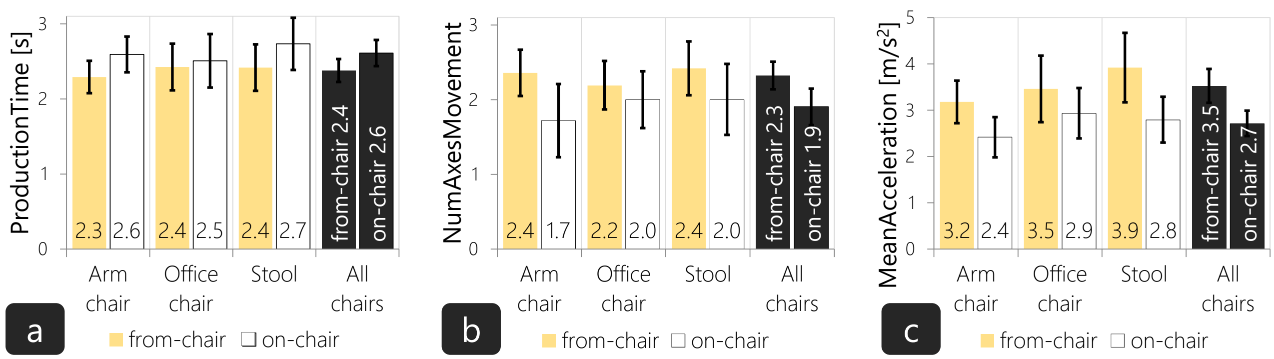


**Figure 4: The kinematic profiles of participants' *on-chair* and *from-chair* gesture articulations, according to ChairType.**

(95.1%). Furthermore, more than half of the ratings for Ease, Recall, and SocialAcceptability (55.8% to 62.7%) as well as 41.0% of the Goodness ratings were maximal (7, strongly agree). We did not observe significant effects of ChairType on any of these measures (all $p$-values>.05, *n.s.*). However, *from-chair* gestures received slightly, yet statistically significant, higher ratings than *on-chair* gestures in terms of Goodness (Mdn=6, M=6.0 vs. Mdn=6, M=5.7, $\chi^2_{(1)}$=40.765, $p$<.001), Ease (Mdn=7, M=6.4 vs. Mdn=7, M=6.3, $\chi^2_{(1)}$=5.557, $p$=.018), and Recall (Mdn=7, M=6.3 vs. Mdn=7, M=6.1, $\chi^2_{(1)}$=26.058, $p$<.001),

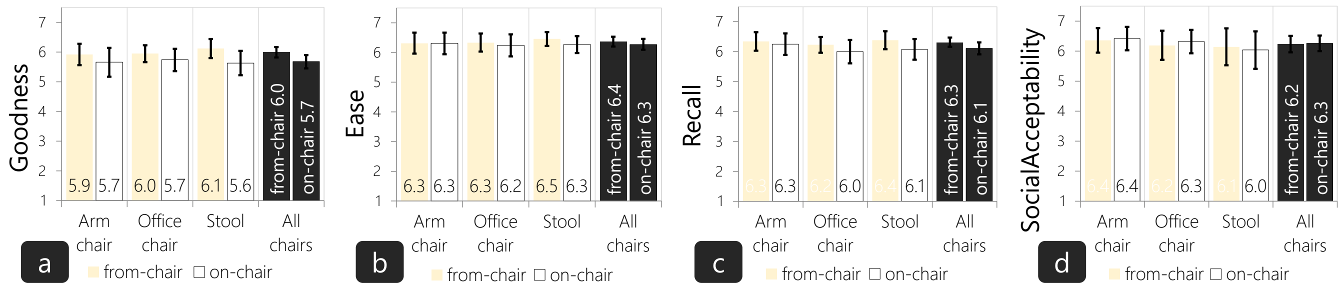


**Figure 5: Participants' self-reported ratings of their *on-chair* and *from-chair* gestures, according to ChairType.**

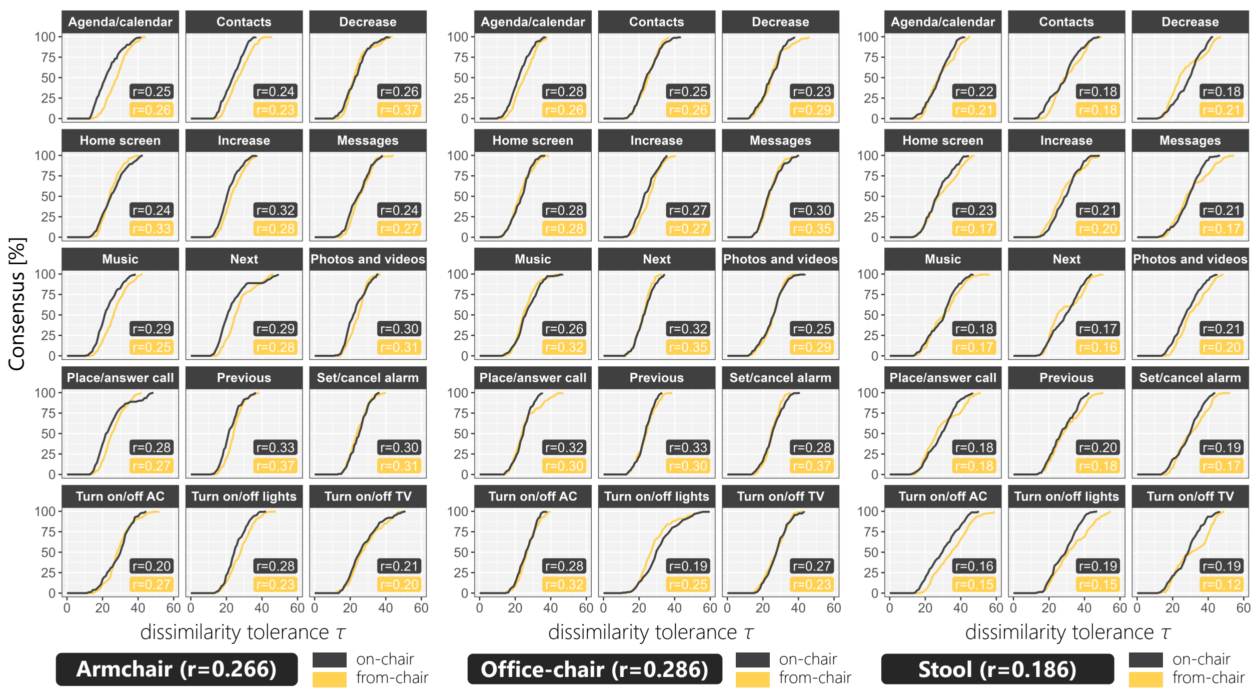


**Figure 6: Dissimilarity-Consensus curves [96] computed with the DTW dissimilarity function for the fifteen referents in our study per ChairType and GestureLocale. *Notes:* larger growth rate $r$ values denote faster reaching consensus among the gestures elicited for the same referent, e.g., $r$=0.33 for "Previous" vs. $r$=0.24 for "Contacts" in the *stool* and *on-chair* conditions.**

but not SocialAcceptability (Mdn=7, M=6.2 vs. Mdn=7, M=6.3, $\chi^2_{(1)}$=1.314, $p$=.252, *n.s.*). One possible explanation for these findings may be that *from-chair* gestures allow for a wider range of hand movements, not constrained to a limited set of locations, more or less distinctive, on the chair. Nevertheless, any observed difference was small in magnitude, amounting to less than 5% in terms of means, while the medians were identical. Referents with directional connotations, e.g., "Next," "Previous," "Increase," and "Decrease," consistently received high Goodness and Ease ratings, while referents for which the elicited gestures mimicked physical interactions, e.g., "Answer call," "Turn on/off lights," "Turn on/off AC," and "Turn on/off TV," were rated highly in terms of Recall.

## 4.4 Consensus Analysis and Representative Hand-Chair Gestures

So far, we mentioned individual referents and the elicited gestures for those referents only sporadically as we considered the referents as random effects in our statistical models, i.e., a sample of all possible referents, used as a vehicle for collecting possible hand-chair gestures that feel intuitive to end users. In the following, we look more closely at the elicited gestures as we are interested in participants' level of consensus ($C$) over suitable gestures to invoke specific referents. To this end, we modeled the dissimilarity-consensus curves of the fifteen referents employed in our study using logistic models (see Subsection 3.3.2 for details about our analysis method) for each combination of ChairType × GestureLocale, and analyzed the growth rates $r$; see Figure 6. (According to [96], larger $r$ values indicate faster reaching consensus among participants' gesture proposals for a specific referent.) We found that the $C_0$ parameters of the logistic functions (Eq. 2) varied between 0.09 and 0.65 and $C_\infty$ between 98.38 and 103.50, showing of a good fit of the derived logistic models; see [96] for details. We did not find a significant effect of GestureLocale on $r$ (0.315 for *on-chair* vs. 0.328 for *from-chair* gestures, $F_{(1,14)}$=0.768, $p$=.396, *n.s.*), indicating similar consensus formation for both *on-chair* and *from-chair* articulations. However, we found a significant effect of ChairType ($F_{(2,28)}$=68.620, $p$<.01), where *stool* gestures (mean $r$=0.186) exhibited significantly less consensus compared to the cases of *office-chair* (0.286) and *armchair* (0.266) gestures (FDR-adjusted $p$'s<.001), but we detected no difference between the *office-chair* and *armchair* ($p$>.05, *n.s.*); see Figure 6 for all of the growth rates computed per ChairType × GestureLocale × Referent categories.

To complement these results, which present the computer perspective [96, 99] on our elicited gestures, we performed a frequential analysis of their qualitative characteristics of Handedness, GestureType, and GestureExtent. This approach enabled us to identify representative gesture characteristics for each Referent and combination of ChairType × GestureLocale, according to the highest frequency observed across possible mixtures of those characteristics. For example, 9 out of the 18 participants in the *stool* condition (9/18=50%) proposed unimanual (1H) hand poses (P) in the periphery (Pe) to effect "Place/answer call" with *from-chair* gestures; see Figure 7.76 for a gesture with these characteristics represented by mimicking holding a phone next to the ear and mouth. The largest frequencies of shared *from-chair* gesture characteristics for the same referent, but in the *armchair* and *office-chair* conditions, were 6 and 5, representing consensus rates of 33% and 28%, respectively; see Figures 7.46 and 7.61. An interesting observation is that, although the winning gesture for "Place/answer call" remained consistent across ChairType, the level of consensus was notably higher in the *stool* condition compared to the more complex form factors of the *office-chair* and *armchair*. This disparity suggests that the participants envisioned different *from-chair* gesture articulation possibilities influenced by the presence of the backrest and armrest, two parts absent in the *stool* design. Besides common winning gesture articulation categories across ChairType, we also observed common categories across GestureLocale, e.g., drawing "letter M," either on the seat or in mid-air for "Messages" (7.38 and 7.83) and drawing a triangular shape for "Music" (7.7 and 7.52).

Stroke gestures, constituting the most frequently occurring category for *from-chair* input, were represented by geometric signs (e.g., Figures 7.52, 7.54, 7.59, 7.79), directional swipes (e.g., 7.57, 7.71, 7.58, 7.89), and letters and symbols (e.g., 7.67, 7.68, 7.77, 7.82). Strokes were also common for *on-chair* articulations as geometric shapes (e.g., 7.5, 7.7, 7.9, 7.35), directional swipes (e.g., 7.10, 7.26, 7.31), and letters and symbols (e.g., 7.24, 7.36, 7.38). Examples of the latter include drawing "letter P" on the front right side of the *stool*'s seat to effect "Photos and videos" (7.36) and drawing the symbol of a house on the seat's side for "Home screen" (7.45). Representative *on-chair* gestures also included touch input with different variations, e.g., tapping with two fingers (7.2), four fingers (7.4), the whole hand (7.3), and tapping multiple times (7.32). The winning *on-chair* gesture categories always involved the armrest in the *armchair* condition (7.1 to 7.15), and were identical for half of the referents for the *on-chair* gestures elicited in the *office-chair* and *stool* conditions, which lacked armrests. Notable examples are the directional referents "Next/Previous" and "Increase/Decrease," which received directional swipes performed on the armrest (7.11 to 7.14) and seat (7.26 to 7.29 and 7.41 to 7.44), according to ChairType. While we provide the gestures from Figure 7 as a representative set of the most frequently occurring articulation characteristics of the hand-chair gestures observed in our study, we also make available a detailed description of all of the 1,620 elicited gestures as part of our open-source gesture dataset for further analyses.

To contextualize these findings, we compare them with the gesture characteristics of two corresponding consensus gesture sets from the literature of end-user elicitation. We contrast our findings regarding the observed characteristics of *on-chair* gestures, a subclass of surface gestures performed in relation to the chair's parts, with the established set of surface gestures reported in Wobbrock *et al.*'s seminal paper on end-user elicitation [108, p. 1089]. We further contrast the characteristics of *from-chair* gestures, a subclass of mid-air gestures performed from the seated position in the space around the chair, with a consensus set of mid-air gestures aggregated across different application domains [36, p. 12]; see Table 3 for details and our results.

Several interesting observations highlight the distinctive nature of hand-chair gestures in this context. For instance, while the large surface of a tabletop encourages more opportunities for using both hands (35.4%), the smaller chair surfaces resulted in none or rare (6.7%) instances of bimanual *on-chair* input in our consensus sets. However, the percentage of bimanual *from-chair* gestures was both notably lower (0% for the *armchair*) and higher (20.0% for the *stool*) than the expected norm (9.1%) of bimanual mid-air gestures [36]. In the context where unimanual gestures are generally preferred due to less effort, this discovery underscores that the *armchair* presented more opportunities for performing *from-chair* unimanual gestures when the participants could see and/or refer to more chair parts, unlike the simpler form factor of a *stool*, where the participants resorted to bimanual input more often. In addition to handedness characteristics, we also noted interesting differences in terms of gesture type; see the final three rows of Table 3. First, none of the consensus *on-chair* gesture characteristics involved hand poses for manipulative purposes, whereas these poses constituted more than half (58.3%) of the in-consensus surface gestures [108]. In contrast, *from-chair* gestures exhibited hand pose percentages close to those observed in the literature (54.5%) [36], except for the *stool*, where most of the *from-chair* gestures involved directional swipes and symbolic strokes. Stroke-gestures were also considerably more common for *on-chair* (46.7% to 80.0%) compared to surface (18.8%) input [108]. To summarize, *on-chair* gestures are almost exclusively unimanual, often involve simple tap input where a chair surface is available to tap on, and involve drawing strokes on accessible chair parts. As for non-contact input, *from-chair* gestures exhibit many similarities to mid-air gestures but, as chair design complexity increases, they involve fewer strokes and favor more hand poses.

## 5 DISCUSSION

In this section, we capitalize on our empirical findings to offer actionable insights for novel hand-chair gesture interactions in the

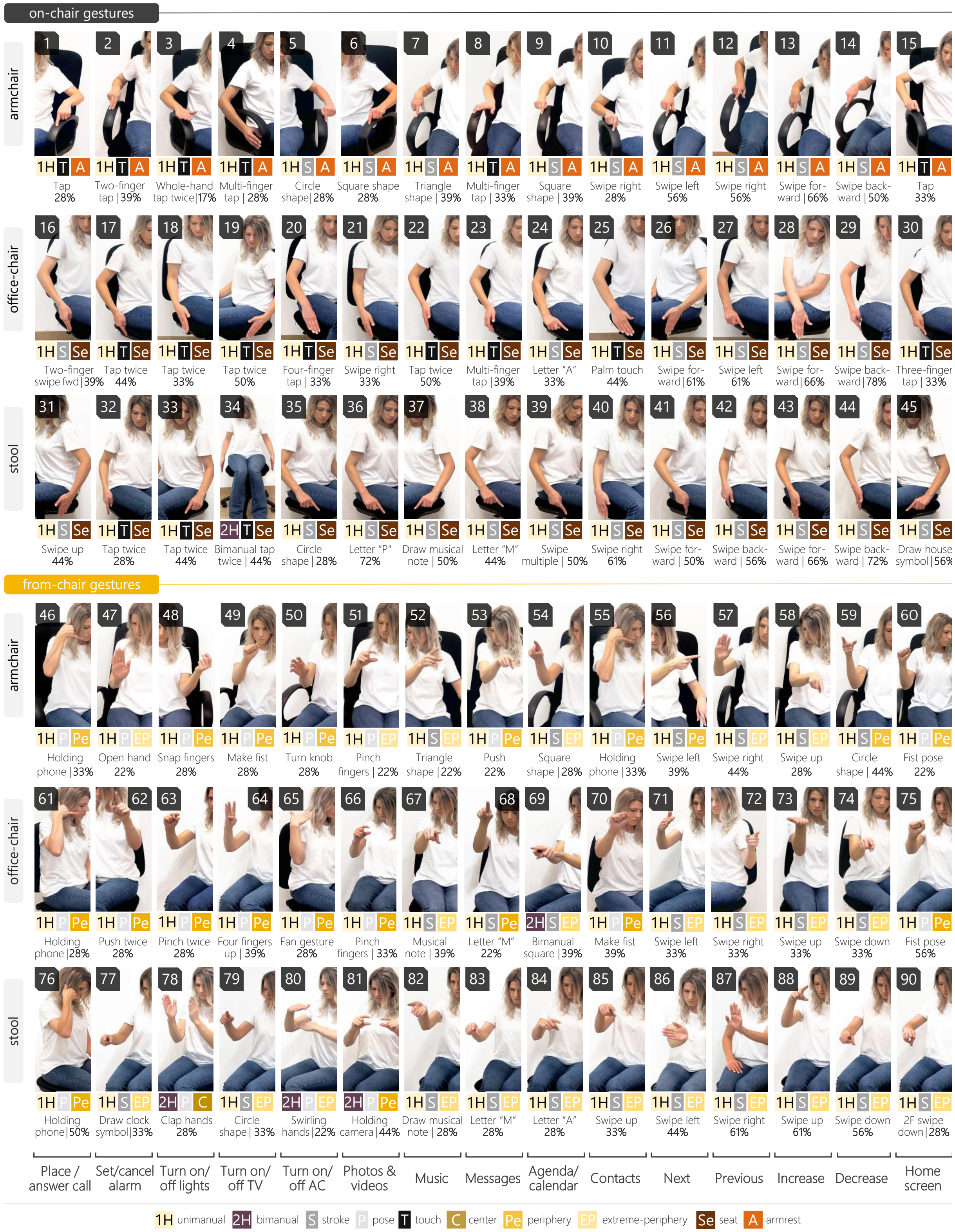


**Figure 7: Representative *on-chair* and *from-chair* gestures per ChairType and Referent. *Notes:* gesture characteristics (e.g., 1H) are indicated below each photo; consensus percentages are calculated across groups of gestures with the same characteristics.**

**Table 3: Hand-chair gesture characteristics vs. two established surface [108] and mid-air [36] consensus gesture sets.**

| Criteria | Surface vs. on-chair gestures | | | | Mid-air vs. from-chair gestures | | | |
|---|---|---|---|---|---|---|---|---|
| | Wobbrock *et al.* [108] | Arm-chair | Office-chair | Stool | Hosseini *et al.* [36] | Arm-chair | Office-chair | Stool |
| Number of referents | 27 | 15 | 15 | 15 | 22 | 15 | 15 | 15 |
| Number of gestures in the consensus set | 48 | 15 | 15 | 15 | 22 | 15 | 15 | 15 |
| Percentage of unimanual gestures | 64.6% | 100% | 100% | 93.3% | 90.9% | 100% | 93.3% | 80.0% |
| Percentage of bimanual gestures | 35.4% | – | – | 6.7% | 9.1% | – | 6.7% | 20.0% |
| Percentage of taps | 22.9% | 40.0% | 53.3% | 20.0% | – | – | – | – |
| Percentage of poses/manipulative gestures[†] | 58.3% | – | – | – | 54.5% | 60.0% | 53.3% | 20.0% |
| Percentage of stroke-gestures | 18.8% | 60.0% | 46.7% | 80.0% | 45.5% | 40.0% | 46.7% | 80.0% |

[†]Both [108] and [36] describe manipulative gestures, which we subsume under the hand poses category; see details about our GestureType measure in Subsection 3.3.

form of six design implications. We also present limitations of our study and outline next steps to address them.

## 5.1 Design Implications for Hand-Chair Gesture Interactions

Before proceeding with our implications, we briefly set their context. Chairs that provide a frame for gesture input fit into the ubiquitous computing paradigm [103], where user sensing is dissimulated into everyday objects. For instance, when applying Poslad's [75] user interface design heuristics for ubicomp environments (*italicized* below) to the specific case of chairs, we find that the distinctive structural elements of a chair favor *self exploration,* turn the chair into a *user interface proxy* to simplify access to multiple individual devices, while the familiar chair form factor provides a *predictable interaction context.* Within this framework, we propose the following set of design implications.

❶ ***Use the chair's structural elements to inform customized on-chair gesture input.*** Our discoveries showed that when armrests are present, they are the preferred choice for *on-chair* input (73.3%). In their absence, the seat becomes the primary choice, accounting for 89.6% in chairs with a backrest and 100% otherwise (Figure 3). Thus, the structural elements of chairs can be leveraged for (i) gesture vocabulary designs that ensure consistency across various chair types by centering on input on the seat—available on all chairs—at the intersection of the consensus sets in Figure 7, but also (ii) designs specific to chair form factors, e.g., armrest gestures, for applications leveraging the convenience of such elements, such as in lean-back interaction [111] when using the armrest as a metaphorical remote control. Additionally, we recommend (iii) exploration of gesture sets that are both chair- and user-dependent, as our dissimilarity-consensus analysis (Figure 6) revealed differences between users' gesture articulations.

❷ ***Leverage the seated position for fast, expressive, and restful from-chair gesture input.*** Our findings revealed that mid-air hand gestures performed from the seated position are fast with an average production time of just 2.4s (Figure 4). Moreover, they utilize the peripersonal space, located in between the center region (closest to the body) and the extreme periphery (farthest away from the body; see Figure 3). In this easily reachable space, *from-chair* gestures predominantly consist of symbolic *stroke-gestures* and expressive *hand poses* (93.3%, Figure 2) in a ratio that depends on the chair type (Table 3). In the light of these findings, we recommend capitalizing on the rich literature of mid-air gesture design [45] to pinpoint high consensus [36] *stroke-gestures* and *hand poses* with articulations that peak in the peripheral region and leverage chairs' parts for restful mid-air interactions [100, 111].

❸ ***Harness the high perceived social acceptability of hand-chair gestures for interactions in public contexts.*** Hand-chair gestures can be used to mitigate concerns [77] regarding the social acceptability of whole-body gestures for chair-based input, such as chair tilting and rotating, as we found high social acceptability for both *on-chair* (6.3 out of 7) and *from-chair* (6.2) gestures (Figure 5). This implication suggests future work where hand-chair gesture UIs are conveniently available in seated public settings, e.g., public transportation, lecture halls, waiting rooms, etc.

❹ ***Play on the complementarity between on-chair and from-chair gestures.*** *On-chair* and *from-chair* gestures exhibit a complementarity that should be exploited for gesture set design. While *on-chair* gestures turn the chair's structural elements into a tangible interface for always-available surface input, *from-chair* gestures add a supplementary layer of interaction beyond the chair's boundaries. This complementarity should be explored for gesture set designs that favor seamless interchangeability of input on the chair and around it. To provide support for this implication, it is worth noting an interesting insight, where 30.2% of the pairs of *on-chair* and *from-chair* gestures elicited for the same referents shared identical Handedness and GestureType characteristics. This implication aligns with Poslad's [75] design heuristics for streamlined input, self exploration, and using predictable contexts in ubicomp environments, which in our case imply that *on-chair* and *from-chair* input could be used interchangeably. We also recommend exploring the combination of *touch* and *stroke-gesture* hybrid input [1] for *on-chair* gestures as well as combined *on-chair* and *from-chair* input, following prior air+touch interaction techniques [10].

❺ ***Conceptualize chairs as always-available input sensing devices.*** Despite prevalent, most current chairs lack user sensing technology, a seamless integration that could significantly enhance their functionality. For example, based on our findings that *stroke-gesture* and *touch input* dominate users' preferences for *on-chair* input (84.9%), we suggest integration of touch sensing into the armrests of everyday chairs, similar to accessible input technology for wheelchair users [8, 56], and into the lateral sides and corners of the seat (Figure 3). Chair designers should consider enlarging these structural elements, without compromising user comfort [68], to accommodate an expanded gesture input area. New chair materials could also be leveraged for touch sensing, such as textile interfaces [6]. Additionally, *from-chair* gestures could be detected with video cameras in armrests to capture gestures above them [111], but also with users' own devices, such as smartwatches for wrist gestures [53] or rings for stroke-gestures [23].

❻ ***Design for multimodal input including hand-chair gestures.*** Our findings revealed a strong preference for unimanual vs. bimanual gestures (86.3% and 13.7%, see Figure 2). An implication of this result is that the other hand, not involved in gesture articulation, is free to operate another device, such as a desktop mouse, a smartphone in mobile contexts of use, or a smartwatch through wrist and motion gestures, which opens up interesting possibilities for multimodal input. In contrast, bimanual gestures (13.7%, with 11.1% being symmetrical 2SH gestures) should be reserved for less frequent tasks where movement symmetry can provide valuable information to the system. Examples include touching both armrests to confirm an important action for the system, directional swiping with both hands to fast-forward while browsing a list, or leveraging the physical distance between the hands of identical poses to control a system parameter, i.e., parameterized gestures [105]. Furthermore, the observed correlation between users' handedness and their preferred gestures suggests the potential for customizing chair input to individual users, similar to how smartwatch UIs can be configured to match the hand they are worn on [81].

## 5.2 Limitations and Next Steps

While our study has yielded valuable first insights into hand-chair gestures, we acknowledge its limitations, and propose next-step examinations to address them. First, since we focused on standard chairs for everyday users, we made the decision of omitting accessibility research on instrumenting wheelchairs. Although this decision delineated a clear scope for various chair designs and everyday users, we see interesting follow-up investigations connecting our scope with accessible input for wheelchair users, e.g., comparing *on-wheelchair* gestures [4, 8] performed by people with mobility impairments with the *on-chair* gestures from our study. Second, our participant sample consisted mostly of males. While females were equally distributed across the three ChairType conditions, their overall representation was low (17%) since we did not intend Gender as an analysis factor in our study. Unfortunately, female representation tends to be low in elicitation studies, with males often outnumbering female participants in a ratio of 2:1 [102, p. 859]. To explore potential gender effects on hand-chair gestures, we recommend replicating our study using a type-7 replication [24] with a balanced representation of genders, and, possibly, a type-8 replication [24] involving an unsupervised context [9]. To support this, we provide our gesture dataset, together with .NET C# code that computes the measures reported in this paper, freely available at http://www.eed.usv.ro/~vatavu/projects/2024-GESTURES-CHAIR. Third, future explorations of other chair designs, e.g., with varying leg configurations, alternative structural elements, and range of materials [20], as well as involving other user populations, e.g., children's playful interactions with computer systems applied to the case of chairs, are recommended to further expand our understanding of hand-chair gesture input.

# 6 CONCLUSION

We conducted an extensive examination of users' preferences and articulation characteristics of hand-chair gestures, which are gestures performed in the chair's space to control interactive systems. Our study, involving 54 participants, yielded very high self-perceived gesture ratings, fast execution times, and insightful findings about users' preferences to articulate hand-chair gestures according to the distinctive structural elements of the chair. We believe that hand-chair gestures have the potential to seamlessly integrate in our daily interactions with computer systems, given the ubiquity of chairs and their multifaceted cultural significance. As we have just started to explore the vast potential of hand-chair gesture input, we look forward to exciting further developments in this direction, while our dataset and resources are readily available to pave the way for other researchers who wish to embark on this journey.

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# REFERENCES

[1] Ahmed Arif, Michel Pahud, Ken Hinckley, and WIlliam Buxton. 2013. A Tap and Gesture Hybrid Method for Authenticating Smartphone Users. In *Proceedings of the 15th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '13)*. ACM, New York, NY, USA, 486–491. https://doi.org/10.1145/2493190.2494435

[2] Claus Atzenbeck. 2014. Interview with Kumiyo Nakakoji. *SIGWEB Newsl.* 2014, Article 1 (jul 2014), 4 pages. https://doi.org/10.1145/2641730.2641731

[3] Peter Bennett, Heidi Hinder, and Kirsten Cater. 2016. Rekindling Imagination in Dementia Care with the Resonant Interface Rocking Chair. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '16)*. ACM, New York, NY, USA, 2020–2026. https://doi.org/10.1145/2851581.2892505

[4] 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. https://doi.org/10.1145/3544548.3580929

[5] Andreas Braun, Sebastian Frank, Martin Majewski, and Xiaofeng Wang. 2015. CapSeat: Capacitive Proximity Sensing for Automotive Activity Recognition. In *Proceedings of the 7th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '15)*. ACM, New York, NY, USA, 225–232. https://doi.org/10.1145/2799250.2799263

[6] Philipp Brauner, Julia van Heek, Martina Ziefle, Nur Al-huda Hamdan, and Jan Borchers. 2017. Interactive FUrniTURE: Evaluation of Smart Interactive Textile Interfaces for Home Environments. In *Proceedings of the 2017 ACM International Conference on Interactive Surfaces and Spaces (ISS '17)*. ACM, New York, NY, USA, 151–160. https://doi.org/10.1145/3132272.3134108

[7] Xiang Cao and Shumin Zhai. 2007. Modeling Human Performance of Pen Stroke Gestures. In *Proceedings of the SIGCHI Conference on Human Factors in*

*Computing Systems (CHI '07)*. ACM, New York, NY, USA, 1495–1504. https://doi.org/10.1145/1240624.1240850

[8] Patrick Carrington, Amy Hurst, and Shaun K. Kane. 2014. The Gest-Rest: A Pressure-Sensitive Chairable Input Pad for Power Wheelchair Armrests. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility (ASSETS '14)*. ACM, New York, NY, USA, 201–208. https://doi.org/10.1145/2661334.2661374

[9] Michael Chamunorwa, Mikolaj P. Wozniak, Susanna Krämer, Heiko Müller, and Susanne Boll. 2023. An Empirical Comparison of Moderated and Unmoderated Gesture Elicitation Studies on Soft Surfaces and Objects for Smart Home Control. *Proc. ACM Hum.-Comput. Interact.* 7, MHCI, Article 198 (sep 2023), 24 pages. https://doi.org/10.1145/3604245

[10] Xiang 'Anthony' Chen, Julia Schwarz, Chris Harrison, Jennifer Mankoff, and Scott E. Hudson. 2014. Air+touch: Interweaving Touch & in-Air Gestures. In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology (UIST '14)*. ACM, New York, NY, USA, 519–525. https://doi.org/10.1145/2642918.2647392

[11] Yi Fei Cheng, Tiffany Luong, Andreas Rene Fender, Paul Streli, and Christian Holz. 2022. ComforTable User Interfaces: Surfaces Reduce Input Error, Time, and Exertion for Tabletop and Mid-air User Interfaces. In *Proceedings of the 2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR '22)*. IEEE, USA, 150–159. https://doi.org/10.1109/ISMAR55827.2022.00029

[12] Rune Haubo B. Christensen. 2022. ordinal—Regression Models for Ordinal Data. https://CRAN.R-project.org/package=ordinal version 2022.11-16.

[13] Rune Haubo Bojesen Christensen. 2023. Package 'ordinal'. Regression Models for Ordinal Data. https://CRAN.R-project.org/package=ordinal. Accessed Dec. 2023.

[14] Mauricio Cirelli and Ricardo Nakamura. 2014. A Survey on Multi-Touch Gesture Recognition and Multi-Touch Frameworks. In *Proceedings of the 9th ACM Int. Conference on Interactive Tabletops and Surfaces (ITS '14)*. ACM, New York, NY, USA, 35–44. https://doi.org/10.1145/2669485.2669509

[15] Ida Damen, Daphne Menheere, Carine Lallemand, and Steven Vos. 2020. Ivy: Reading a Critical Design for Sedentary Behavior in the Office Context. In *Companion Publication of the 2020 ACM Designing Interactive Systems Conference (DIS' 20 Companion)*. ACM, New York, NY, USA, 7–12. https://doi.org/10.1145/3393914.3395893

[16] Carlos Henrique De Aguiar, Reza Fateminasab, Chase G. Frazelle, Ryan Scott, Yixiao Wang, Michael B. Wooten, Keith E. Green, and Ian D. Walker. 2016. The Networked, Robotic Home+ Furniture Suite: A Distributed, Assistive Technology Facilitating Aging in Place. In *Proceedings of the 2016 IEEE International Conference on Automation Science and Engineering (CASE '16)*. IEEE, USA, 1067–1072. https://doi.org/10.1109/COASE.2016.7743522

[17] Florence de Dampierre. 2006. *Chairs: A History*. Harry N. Abrams, Inc., New York, NY, USA.

[18] Alex Endert, Patrick Fiaux, Haeyong Chung, Michael Stewart, Christopher Andrews, and Chris North. 2011. ChairMouse: Leveraging Natural Chair Rotation for Cursor Navigation on Large, High-Resolution Displays. In *CHI '11 Extended Abstracts on Human Factors in Computing Systems (CHI EA '11)*. ACM, New York, NY, USA, 571–580. https://doi.org/10.1145/1979742.1979628

[19] Jheanel E. Estrada and Larry A. Vea. 2020. Real-Time Human Sitting Position Recognition Using Wireless Sensors. In *Proceedings of the 2nd International Conference on Image, Video and Signal Processing (IVSP '20)*. ACM, New York, NY, USA, 133–137. https://doi.org/10.1145/3388818.3393714

[20] Charlotte Fiell and Peter Fiell. 2017. *1000 Chairs*. Taschen America, Los Angeles, CA, USA. https://www.taschen.com/en/books/architecture-design/49357/1000-chairs-revised-and-updated-edition/

[21] Jacob Freiberg, Alexandra Kitson, and Bernhard E. Riecke. 2017. Development and Evaluation of a Hands-Free Motion Cueing Interface for Ground-based Navigation. In *Proceedings of IEEE Virtual Reality (VR '17)*. IEEE, USA, 273–274. https://doi.org/10.1109/VR.2017.7892282

[22] Ferdinand Fuhrmann and Rene Kaiser. 2014. Multimodal Interaction for Future Control Centers: An Interactive Demonstrator. In *Proceedings of the 16th International Conference on Multimodal Interaction (ICMI '14)*. ACM, New York, NY, USA, 66–67. https://doi.org/10.1145/2663204.2669620

[23] Bogdan-Florin Gheran, Jean Vanderdonckt, and Radu-Daniel Vatavu. 2018. Gestures for Smart Rings: Empirical Results, Insights, and Design Implications. In *Proceedings of the Designing Interactive Systems Conference (DIS '18)*. ACM, New York, NY, USA, 623–635. https://doi.org/10.1145/3196709.3196741

[24] Bogdan-Florin Gheran, Santiago Villarreal-Narvaez, Radu-Daniel Vatavu, and Jean Vanderdonckt. 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 2022)*. ACM, New York, NY, USA, Article 5, 9 pages. https://doi.org/10.1145/3531073.3531112

[25] Yolanda Gil. 2020. Keynote Speaker: Yolanda Gil. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD '20)*. ACM, New York, NY, USA, 4. https://doi.org/10.1145/3394486.3407094

[26] Daniele Giunchi, Alejandro Sztrajman, Stuart James, and Anthony Steed. 2021. Mixing Modalities of 3D Sketching and Speech for Interactive Model Retrieval in Virtual Reality. In *Proceedings of the ACM International Conference on Interactive Media Experiences (IMX '21)*. ACM, New York, NY, USA, 144–155. https://doi.org/10.1145/3452918.3458806

[27] Google for Developers. 2023. SensorEvent | Android Developers. https://developer.android.com/reference/android/hardware/SensorEvent. Accessed Dec. 2023.

[28] Ge Guo, Gilly Leshed, Trevor Pinch, and Keith Evan Green. 2022. SocialStools: A Playful, Socio-Spatial Interface for Fostering Togetherness Across Strangers. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems (CHI EA '22)*. ACM, New York, NY, USA, Article 173, 5 pages. https://doi.org/10.1145/3491101.3519877

[29] Kilem Li Gwet. 2010. Computing Inter-Rater Reliability and its Variance in the Presence of High Agreement. *Brit. J. Math. Statist. Psych.* 61 (2010), 29–48. https://doi.org/10.1348/000711006X126600

[30] Kilem Li Gwet. 2019. irrCAC-benchmarking. https://cran.r-project.org/web/packages/irrCAC/vignettes/benchmarking.html. Accessed Dec. 2023.

[31] Abraham M. Hashemian, Ashu Adhikari, Ernst Kruijff, Markus von der Heyde, and Bernhard E. Riecke. 2023. Leaning-Based Interfaces Improve Ground-Based VR Locomotion in Reach-the-Target, Follow-the-Path, and Racing Tasks. *IEEE Transactions on Visualization and Computer Graphics* 29, 3 (2023), 1748–1768. https://doi.org/10.1109/TVCG.2021.3131422

[32] Abraham M. Hashemian, Matin Lotfaliei, Ashu Adhikari, Ernst Kruijff, and Bernhard E. Riecke. 2022. HeadJoystick: Improving Flying in VR Using a Novel Leaning-Based Interface. *IEEE Transactions on Visualization and Computer Graphics* 28, 4 (2022), 1792–1809. https://doi.org/10.1109/TVCG.2020.3025084

[33] Sunao Hashimoto, Ryohei Suzuki, Youichi Kamiyama, Masahiko Inami, and Takeo Igarashi. 2013. LightCloth: Senseable Illuminating Optical Fiber Cloth for Creating Interactive Surfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 603–606. https://doi.org/10.1145/2470654.2470739

[34] Feng Hong, Shujuan You, Meiyu Wei, Yongtuo Zhang, and Zhongwen Guo. 2016. MGRA: Motion Gesture Recognition via Accelerometer. *Sensors* 16, 4 (2016), 530. https://doi.org/10.3390/s16040530

[35] Mark Hopkins and Jocelyn Berrendonner. 2023. Accelerometer thresholds. https://docs.microsoft.com/en-us/windows-hardware/drivers/sensors/accelerometer-thresholds. Accessed Dec. 2023.

[36] 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. https://doi.org/10.1145/3544548.3581420

[37] Hessam Jahani and Manolya Kavakli. 2018. Exploring a User-Defined Gesture Vocabulary for Descriptive Mid-air Interactions. *Cognition, Technology & Work* 20 (2018), 11–22. https://doi.org/10.1007/s10111-017-0444-0

[38] Sujin Jang, Wolfgang Stuerzlinger, Satyajit Ambike, and Karthik Ramani. 2017. Modeling Cumulative Arm Fatigue in Mid-Air Interaction Based on Perceived Exertion and Kinetics of Arm Motion. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 3328–3339. https://doi.org/10.1145/3025453.3025523

[39] 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. https://doi.org/10.1145/1978942.1979001

[40] Md. Nafiz Hasan Khan, Carman Neustaedter, and Alissa Antle. 2019. Flight Chair: An Interactive Chair for Controlling Emergency Service Drones. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems (CHI EA '19)*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3290607.3313031

[41] 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. *Int. J. of Human-Computer Studies* 69, 11 (2011), 693–704. https://doi.org/10.1016/j.ijhcs.2011.04.005

[42] Alexandra Kitson, Abraham M. Hashemian, Ekaterina R. Stepanova, Ernst Kruijff, and Bernhard E. Riecke. 2017. Comparing Leaning-based Motion Cueing Interfaces for Virtual Reality Locomotion. In *Proceedings of the 2017 IEEE Symposium on 3D User Interfaces (3DUI '17)*. IEEE, USA, 73–82. https://doi.org/10.1109/3DUI.2017.7893320

[43] Alexandra Kitson, Abraham M. Hashemian, Ekaterina R. Stepanova, Ernst Kruijff, and Bernhard E. Riecke. 2017. Lean Into It: Exploring Leaning-based Motion Cueing Interfaces for Virtual Reality Movement. In *Proceedings of IEEE Virtual Reality (VR '17)*. IEEE, USA, 215–216. https://doi.org/10.1109/VR.2017.7892253

[44] Alexandra Kitson, Bernhard E. Riecke, Abraham M. Hashemian, and Carman Neustaedter. 2015. NaviChair: Evaluating an Embodied Interface Using a Pointing Task to Navigate Virtual Reality. In *Proceedings of the 3rd ACM Symposium on Spatial User Interaction (SUI '15)*. ACM, New York, NY, USA, 123–126. https://doi.org/10.1145/2788940.2788956

[45] Panayiotis Koutsabasis and Panagiotis Vogiatzidakis. 2019. Empirical Research in Mid-Air Interaction: A Systematic Review. *International Journal of Human–Computer Interaction* 35, 18 (2019), 1747–1768. https://doi.org/10.1080/10447318.2019.1572352

[46] Sven Kratz and Jason Wiese. 2016. GestureSeg: Developing a Gesture Segmentation System Using Gesture Execution Phase Labeling by Crowd Workers. In *Proceedings of the 8th ACM SIGCHI Symposium on Engineering Interactive Computing Systems (EICS '16)*. ACM, New York, NY, USA, 61–72. https://doi.org/10.1145/2933242.2933261

[47] Mike Lambeta, Matt Dridger, Paul White, Jesslyn Janssen, and Ahmad Byagowi. 2016. Haptic Wheelchair. In *ACM SIGGRAPH 2016 Posters (SIGGRAPH '16)*. ACM, New York, NY, USA, Article 90, 2 pages. https://doi.org/10.1145/2945078.2945168

[48] Sang-Su Lee, Jeonghun Chae, Hyunjeong Kim, Youn-kyung Lim, and Kun-pyo Lee. 2013. Towards More Natural Digital Content Manipulation via User Freehand Gestural Interaction in a Living Room. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '13)*. ACM, New York, NY, USA, 617–626. https://doi.org/10.1145/2493432.2493480

[49] Sang-Su Lee, Sohyun Kim, Bopil Jin, Eunji Choi, Boa Kim, Xu Jia, Daeeop 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. https://doi.org/10.1145/1753326.1753572

[50] Young Suk Lee and Daniel Saakes. 2021. "Footsie": Exploring Physical Human-Machine-Interaction through Flirtatious Furniture. In *Proceedings of the 15th International Conference on Tangible, Embedded, and Embodied Interaction (TEI '21)*. ACM, New York, NY, USA, Article 79, 4 pages. https://doi.org/10.1145/3430524.3444639

[51] Young Suk Lee and Daniel Saakes. 2022. "Tête-à-Tête 22": Mediating Intimate Relationship through Expressive Digital Interaction. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems (CHI EA '22)*. ACM, New York, NY, USA, Article 194, 4 pages. https://doi.org/10.1145/3491101.3519889

[52] Luis A. Leiva, Daniel Martín-Albo, Réjean Plamondon, and Radu-Daniel Vatavu. 2018. KeyTime: Super-Accurate Prediction of Stroke Gesture Production Times. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, New York, NY, USA, Article 239, 12 pages. https://doi.org/10.1145/3173574.3173813

[53] Qi Feng Liu, Keiko Katsuragawa, and Edward Lank. 2019. Eliciting Wrist and Finger Gestures to Guide Recognizer Design. In *Proceedings of Graphics Interface (GI '19)*. Canadian Information Processing Society, Canada, 9 pages. https://doi.org/10.20380/GI2019.09

[54] David Mace, Wei Gao, and Ayse Coskun. 2013. Accelerometer-Based Hand Gesture Recognition Using Feature Weighted Naïve Bayesian Classifiers and Dynamic Time Warping. In *Companion Publication of the 2013 International Conference on Intelligent User Interfaces (IUI '13 Companion)*. ACM, New York, NY, USA, 83–84. https://doi.org/10.1145/2451176.2451211

[55] Nathan Magrofuoco, Paolo Roselli, and Jean Vanderdonckt. 2021. Two-Dimensional Stroke Gesture Recognition: A Survey. *ACM Comput. Surv.* 54, 7, Article 155 (jul 2021), 36 pages. https://doi.org/10.1145/3465400

[56] Meethu Malu and Leah Findlater. 2015. Personalized, Wearable Control of a Head-Mounted Display for Users with Upper Body Motor Impairments. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. ACM, New York, NY, USA, 221–230. https://doi.org/10.1145/2702123.2702188

[57] Charles E. Matthews, Kong Y. Chen, Patty S. Freedson, Maciej S. Buchowski, Bettina M. Beech, Russell R. Pate, and Richard P. Troiano. 2008. Amount of Time Spent in Sedentary Behaviors in the United States, 2003-2004. *Am J Epidemiol.* 167, 7 (2008), 875–881. https://doi.org/10.1093/aje/kwm390

[58] Slavomir Matuska, Martin Paralic, Robert Hudec, and Ondrej Krejcar. 2020. A Smart System for Sitting Posture Detection Based on Force Sensors and Mobile Application. *Mobile Information Systems* 2020 (jan 2020), 13 pages. https://doi.org/10.1155/2020/6625797

[59] David McNeill. 1992. *Hand and Mind: What Gestures Reveal About Thought.* Vol. 27. University of Chicago Press, Chicago, IL, USA. https://worldcat.org/en/title/24379126

[60] Daphne Menheere, Ida Damen, Carine Lallemand, and Steven Vos. 2020. Ivy: A Qualitative Interface to Reduce Sedentary Behavior in the Office Context. In *Companion Publication of the 2020 ACM Designing Interactive Systems Conference (DIS' 20 Companion)*. ACM, New York, NY, USA, 329–332. https://doi.org/10.1145/3393914.3395822

[61] Sari Merilampi, Kyle Mulholland, Venni Ihanakangas, Jonna Ojala, Pauli Valo, and Johanna Virkki. 2019. A Smart Chair Physiotherapy Exergame for Fall Prevention – User Experience Study. In *Proceedings of the 7th IEEE International Conference on Serious Games and Applications for Health (SeGAH '19)*. IEEE, USA, 1–5. https://doi.org/10.1109/SeGAH.2019.8882482

[62] Matthew Mosher, David Tinapple, Enrique Tomas, Keina Konno, Richi Owaki, Yoshito Onishi, Ryo Kanda, Sheep, Akiko Takeshita, Tsubasa Nishi, Naoko Shiomi, Kyle McDonald, Satoru Higa, Kazuhiro Jo, Yoko Ando, Kazunao Abe, Takayuki Ito, Shannon Cuykendall, Ethan Soutar-Rau, and Thecla Schiphorst. 2016. Demo Hour. *Interactions* 23, 3 (apr 2016), 8–11. https://doi.org/10.1145/2904383

[63] Bilge Mutlu, Andreas Krause, Jodi Forlizzi, Carlos Guestrin, and Jessica Hodgins. 2007. Robust, Low-Cost, Non-Intrusive Sensing and Recognition of Seated Postures. In *Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology (UIST '07)*. ACM, New York, NY, USA, 149–158. https://doi.org/10.1145/1294211.1294237

[64] Miguel A. Nacenta, Yemliha Kamber, Yizhou Qiang, and Per Ola Kristensson. 2013. Memorability of Pre-Designed and User-Defined Gesture Sets. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, New York, NY, USA, 1099–1108. https://doi.org/10.1145/2470654.2466142

[65] Masashi Okubo and Aya Fujimura. 2009. A Proposal of Estimation System for Concentration Situation by Using Acceleration Sensor. In *Proceedings of the 18th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN '09)*. IEEE, USA, 498–503. https://doi.org/10.1109/ROMAN.2009.5326219

[66] Takeshi Oozu, Aki Yamada, Yuki Enzaki, and Hiroo Iwata. 2016. Escaping Chair: Furniture-Shaped Device Art. In *ACM SIGGRAPH 2016 Posters (SIGGRAPH '16)*. ACM, New York, NY, USA, Article 8, 2 pages. https://doi.org/10.1145/2945078.2945086

[67] Takeshi Oozu, Aki Yamada, Yuki Enzaki, and Hiroo Iwata. 2017. Escaping Chair: Furniture-Shaped Device Art. In *Proceedings of the 11th International Conference on Tangible, Embedded, and Embodied Interaction (TEI '17)*. ACM, New York, NY, USA, 403–407. https://doi.org/10.1145/3024969.3025064

[68] Julius Panero and Martin Zelnik. 1979. *Human Dimension & Interior Space: A Source Book of Design Reference Standards.* Watson-Guptill Publications, New York, NY, USA. https://worldcat.org/title/5411702

[69] Thomas V. Papakostas. 2006. Tactile Sensing in Intelligent Environments. In *Proceedings of the 2nd IET International Conference on Intelligent Environments (IE '06)*. IET Digital Library, USA, 321. https://doi.org/10.1049/cp:20060658

[70] Dimitris Papanikolaou, A.J. Bernheim Brush, and Asta Roseway. 2015. BodyPods: Designing Posture Sensing Chairs for Capturing and Sharing Implicit Interactions. In *Proceedings of the 9th International Conference on Tangible, Embedded, and Embodied Interaction (TEI '15)*. ACM, New York, NY, USA, 375–382. https://doi.org/10.1145/2677199.2680591

[71] Eva L. Parkhurst, Fernando Montalvo, Aman Behal, and Janan A. Smither. 2018. Heuristic Evaluation of Compensations for a Wheelchair Mounted Robotic Arm. In *Proceedings of the Technology, Mind, and Society (TechMindSociety '18)*. ACM, New York, NY, USA, Article 29, 1 pages. https://doi.org/10.1145/3183654.3183677

[72] Anand Paul, Soon Ki Jung, Awais Ahmad, and Ganesh Kumar. 2019. Session Details: Theme: AI and Agents: HCI - Smart Human Computer Interaction Track. In *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing (SAC '19)*. ACM, New York, NY, USA, 1 pages. https://doi.org/10.1145/3329370

[73] Thammathip Piumsomboon, Adrian Clark, Mark Billinghurst, and Andy Cockburn. 2013. User-Defined Gestures for Augmented Reality. In *Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. ACM, New York, NY, USA, 955–960. https://doi.org/10.1145/2468356.2468527

[74] Katrin Plaumann, David Lehr, and Enrico Rukzio. 2016. Who Has the Force? Solving Conflicts for Multi User Mid-Air Gestures for TVs. In *Proceedings of the ACM International Conference on Interactive Experiences for TV and Online Video (TVX '16)*. ACM, New York, NY, USA, 25–29. https://doi.org/10.1145/2932206.2932208

[75] Stefan Poslad. 2009. *Ubiquitous Computing: Smart Devices, Environments and Interactions.* John Wiley & Sons, United Kingdom. https://doi.org/10.1002/9780470779446

[76] Kathrin Probst, David Lindlbauer, Patrick Greindl, Markus Trapp, Michael Haller, Bernhard Schwartz, and Andreas Schrempf. 2013. Rotating, Tilting, Bouncing: Using an Interactive Chair to Promote Activity in Office Environments. In *Extended Abstracts on Human Factors in Computing Systems (CHI EA '13)*. ACM, New York, NY, USA, 79–84. https://doi.org/10.1145/2468356.2468372

[77] Kathrin Probst, David Lindlbauer, Michael Haller, Bernhard Schwartz, and Andreas Schrempf. 2014. A Chair as Ubiquitous Input Device: Exploring Semaphoric Chair Gestures for Focused and Peripheral Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '14)*. ACM, New York, NY, USA, 4097–4106. https://doi.org/10.1145/2556288.2557051

[78] Julie Rico and Stephen Brewster. 2010. Usable Gestures for Mobile Interfaces: Evaluating Social Acceptability. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10)*. ACM, New York, NY, USA, 887–896. https://doi.org/10.1145/1753326.1753458

[79] 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. https://doi.org/10.1145/1978942.1978971

[80] Witold Rybczynski. 2016. *Now I Sit Me Down. From Klismos to Plastic Chair: A Natural History.* Farrar, Straus and Giroux, New York, NY, USA. https://worldcat.org/en/title/919105882

[81] Samsung. 2023. Change the Screen Orientation on Your Galaxy Watch with Wear OS. https://www.samsung.com/us/support/answer/ANS00090382. Accessed Dec. 2023.

[82] Akira Sasou. 2008. Head-Orientation-Estimation-Integrated Speech Recognition for the Smart-Chair. In *Proceedings of the 2nd International Symposium on Universal Communication*. IEEE, USA, 482–489. https://doi.org/10.1109/ISUC.2008.44

[83] Ovidiu-Andrei Schipor and Radu-Daniel Vatavu. 2018. Invisible, Inaudible, and Impalpable: Users' Preferences and Memory Performance for Digital Content in Thin Air. *IEEE Pervasive Computing* 17, 04 (2018), 76–85. https://doi.org/10.1109/MPRV.2018.2873856

[84] Seiichi Serikawa and Lifeng Zhang. 2011. Proposal of a Touch Panel Switch with the Function of Bending and Addition - One of a New User Interface. In *Proceedings of the 2nd International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering*. IEEE, USA, 8–13. https://doi.org/10.1109/ICICI-BME.2011.6108580

[85] Andy P. Siddaway, Alex M. Wood, and Larry V. Hedges. 2019. How to Do a Systematic Review: A Best Practice Guide for Conducting and Reporting Narrative Reviews, Meta-Analyses, and Meta-Syntheses. *Annual Review of Psychology* 70, 1 (2019), 747–770. https://doi.org/10.1146/annurev-psych-010418-102803

[86] Alexandru-Ionut Siean, Cristian Pamparau, Arthur Sluÿters, Radu-Daniel Vatavu, and Jean Vanderdonckt. 2023. Flexible Gesture Input with Radars: Systematic Literature Review and Taxonomy of Radar Sensing Integration in Ambient Intelligence Environments. *Journal of Ambient Intelligence and Humanized Computing* 14 (2023), 7967–7981. https://doi.org/10.1007/s12652-023-04606-9

[87] Sahil Singh Sodhi, Akash Singh Kunwar, Karan Dhingra, and G Suganya. 2017. Smart Chair. In *Proceedings of the 2017 International Conference on Inventive Computing and Informatics (ICICI '17)*. IEEE, USA, 139–148. https://doi.org/10.1109/ICICI.2017.8365324

[88] Tap Systems, Inc. 2023. https://www.tapwithus.com/product/tap-strap-2. Accessed Dec. 2023.

[89] Eugene M. Taranta II, Amirreza Samiei, Mehran Maghoumi, Pooya Khaloo, Corey R. Pittman, and Joseph J. LaViola Jr. 2017. Jackknife: A Reliable Recognizer with Few Samples and Many Modalities. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, New York, NY, USA, 5850–5861. https://doi.org/10.1145/3025453.3026002

[90] Shan-Yuan Teng, Da-Yuan Huang, Chi Wang, Jun Gong, Teddy Seyed, Xing-Dong Yang, and Bing-Yu Chen. 2019. Aarnio: Passive Kinesthetic Force Output for Foreground Interactions on an Interactive Chair. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, Article 672, 13 pages. https://doi.org/10.1145/3290605.3300902

[91] Reena Tripathi and Bindu Verma. 2023. Survey on Vision-based Dynamic Hand Gesture Recognition. *The Visual Computer* (2023), 1–29. https://doi.org/10.1007/s00371-023-03160-x

[92] Emily N. Ussery, Geoffrey P. Whitfield, Janet E. Fulton, Deborah A. Galuska, Charles E. Matthews, Peter T. Katzmarzyk, and Susan A. Carlson. 2021. Trends in Self-Reported Sitting Time by Physical Activity Levels Among US Adults, NHANES 2007/2008-2017/2018. *Journal of Physical Activity and Health* 18, S1 (2021), S74–S83. https://doi.org/10.1123/jpah.2021-0221

[93] Julien Valentin, Vibhav Vineet, Ming-Ming Cheng, David Kim, Jamie Shotton, Pushmeet Kohli, Matthias Nießner, Antonio Criminisi, Shahram Izadi, and Philip Torr. 2015. SemanticPaint: Interactive Segmentation and Learning of 3D World. In *ACM SIGGRAPH 2015 Talks (SIGGRAPH '15)*. ACM, New York, NY, USA, Article 75, 1 pages. https://doi.org/10.1145/2775280.2792589

[94] Jeroen Vanattenhoven, David Geerts, Jean Vanderdonckt, and Jorge-Luis Pérez-Medina. 2019. The Impact of Comfortable Viewing Positions on Smart TV Gestures. In *Proceedings of the 2019 International Conference on Information Systems and Computer Science (INCISCOS '19)*. IEEE, USA, 296–303. https://doi.org/10.1109/INCISCOS49368.2019.00054

[95] Radu-Daniel Vatavu. 2013. A Comparative Study of User-Defined Handheld vs. Freehand Gestures for Home Entertainment Environments. *Journal of Ambient Intelligence and Smart Environments* 5, 2 (2013), 187–211. https://doi.org/10.3233/AIS-130200

[96] 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. https://doi.org/10.1145/3290605.3300454

[97] 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. https://doi.org/10.1145/3544548.3580928

[98] Radu-Daniel Vatavu and Ovidiu-Ciprian Ungurean. 2022. Understanding Gesture Input Articulation with Upper-Body Wearables for Users with Upper-Body Motor Impairments. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (CHI '22)*. ACM, New York, NY, USA, Article 2, 16 pages. https://doi.org/10.1145/3491102.3501964

[99] 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. https://doi.org/10.1145/3476101

[100] Rafael Veras, Gaganpreet Singh, Farzin Farhadi-Niaki, Ritesh Udhani, Parth Pradeep Patekar, Wei Zhou, Pourang Irani, and Wei Li. 2021. Elbow-Anchored Interaction: Designing Restful Mid-Air Input. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. ACM, New York, NY, USA, Article 737, 15 pages. https://doi.org/10.1145/3411764.3445546

[101] Santiago Villarreal-Narvaez, Arthur Sluÿters, Jean Vanderdonckt, 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 (jan 2024), 55 pages. https://doi.org/10.1145/3636458

[102] Santiago Villarreal-Narvaez, Jean Vanderdonckt, 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. https://doi.org/10.1145/3357236.3395511

[103] Mark Weiser. 1999. The Computer for the 21st Century. *SIGMOBILE Mob. Comput. Commun. Rev.* 3, 3 (jul 1999), 3–11. https://doi.org/10.1145/329124.329126

[104] Daniel Wigdor and Dennis Wixon. 2011. *Brave NUI World: Designing Natural User Interfaces for Touch and Gesture* (1st ed.). Morgan Kaufmann Publishers Inc., San Francisco, CA, USA. https://dl.acm.org/doi/10.5555/1995309

[105] Andrew D. Wilson and Aaron F. Bobick. 1999. Parametric Hidden Markov Models for Gesture Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 21, 9 (1999), 884–900. https://doi.org/10.1109/34.790429

[106] Jacob O. Wobbrock, Htet Htet Aung, Brandon Rothrock, and Brad A. Myers. 2005. Maximizing the Guessability of Symbolic Input. In *CHI '05 Extended Abstracts on Human Factors in Computing Systems (CHI EA '05)*. ACM, New York, NY, USA, 1869–1872. https://doi.org/10.1145/1056808.1057043

[107] Jacob O. Wobbrock and Julie A. Kientz. 2016. Research Contributions in Human-Computer Interaction. *Interactions* 23, 3 (April 2016), 38–44. https://doi.org/10.1145/2907069

[108] 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. https://doi.org/10.1145/1518701.1518866

[109] Haijun Xia, Michael Glueck, Michelle Annett, Michael Wang, and Daniel Wigdor. 2022. Iteratively Designing Gesture Vocabularies: A Survey and Analysis of Best Practices in the HCI Literature. *ACM Trans. Comput.-Hum. Interact.* 29, 4, Article 37 (2022), 54 pages. https://doi.org/10.1145/3503537

[110] Lin Yang, Chao Cao, Elizabeth D. Kantor, Long H. Nguyen, Xiaobin Zheng, Yikyung Park, Edward L. Giovannucci, Charles E. Matthews, Graham A. Colditz, and Yin Cao. 2019. Trends in Sedentary Behavior Among the US Population, 2001-2016. *JAMA* 321, 16 (04 2019), 1587–1597. https://doi.org/10.1001/jama.2019.3636

[111] Ionuţ-Alexandru Zaiţi, Ştefan Gheorghe Pentiuc, and Radu-Daniel Vatavu. 2015. On Free-Hand TV Control: Experimental Results on User-Elicited Gestures with Leap Motion. *Personal and Ubiquitous Computing* 19, 5-6 (2015), 821–838. https://doi.org/10.1007/s00779-015-0863-y