

Investigating Unintended Inputs for One-Handed Touch Interaction Beyond the Touchscreen

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ABSTRACT

Additional input controls such as fingerprint scanners, physical buttons, and Back-of-Device (BoD) touch panels improve the input capabilities on smartphones. While previous work showed the benefits of input beyond the touchscreen, unfavorably designed input controls force detrimental grip changes and increase the likelihood of unintended inputs. Researchers investigated all fingers' comfortable areas to avoid grip changes. However, there is no understanding of unintended BoD inputs which frustrate users and lead to embarrassing mistakes. In this paper, we study the BoD areas in which unintended inputs occur during interaction with the touchscreen. Participants performed common tasks on four smartphones which they held in the prevalent single-handed grip while sitting and walking. We recorded finger movements with a motion capture system and analyzed the unintended inputs. We identified comfortable areas on the back in which no unintended inputs occur and found that the least unintended inputs occurred on 5" devices. We derive three design implications for BoD input to help designers considering reachability and unintended input.

CCS CONCEPTS

• **Human-centered computing** → *Interaction techniques*.

KEYWORDS

Finger movement, touch, smartphone, one-handed.

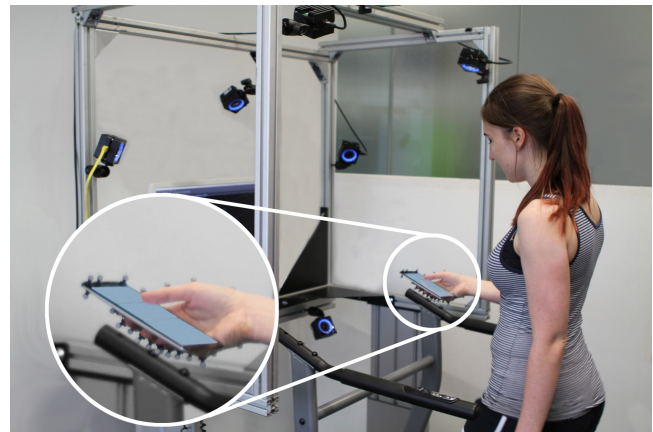


Figure 1: A participant interacting with a smartphone while the hand is being tracked by a motion capture system.

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1 INTRODUCTION

Virtually every smartphone offers input controls beyond the touchscreen. Physical buttons provide shortcuts to change the device volume and power state while fingerprint scanners enable authentication and Back-of-Device (BoD) gestures. Recent smartphones offer an increasing number of further input controls distributed over the whole device surface including buttons for the device assistant, silent switches, and even secondary touchscreens (e.g., ZTE Nubia X). These input controls enable a wide range of promising use cases ranging from shortcuts [50, 53, 56, 58], increasing the thumb's reachability [29, 70], and solving the fat-finger problem [3, 68], through adaptive interfaces [8, 10, 11, 32] and action modifiers [34] based on hand grips, to even enabling finger-aware input on the whole device surface [34]. With foldable smartphones recently emerging, interacting on the whole device surface will soon be possible even on mass-market devices.

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Additional input controls beyond the touchscreen clearly improve mobile interaction but also pose new challenges. When using a smartphone in the prevalent single-handed grip [14, 26, 27, 47], the same hand is used for holding and interacting with the device. This limits the fingers' range and generates unintended inputs due to the continuous contact with the device [37]. The reachability problem can be solved by placing input controls within the *comfortable areas*. For individual fingers in a single-handed grip, Le et al. [33] empirically determined their *comfortable areas* which can be reached without a grip shift. Reducing grip shifts improves the usability of BoD input and avoids that users might drop the device. However, without avoiding unintended inputs, users could make sensitive and detrimental mistakes while using the device. This leads to frustration [7] and renders all BoD input techniques ineffective. Indeed, BoD fingers perform *supportive micro-movements* while the thumb moves on the front side. These are necessary to maintain a stable grip [14, 15], increase the thumb's range [9, 14], and due to the limited independence of the finger movements [18].

Avoiding unintended inputs is vital for the usability of BoD input. An important basis to minimize unintended inputs is an understanding of *supportive micro-movements* which occur while holding and interacting with the device. Previous work analyzed *supportive micro-movements* by quantifying the amount of grip shifts on different smartphones through video observations [13, 14] and built-in IMUs [9, 14, 15]. However, we have no understanding of how fingers move and unintended inputs that they would generate on the rear. In short, unintended inputs are touch events that are considered as input by the device but are not intended by the user. To help designers minimizing unintended BoD inputs, we need to understand the areas in which *supportive micro-movements* occur and the fingers' behavior within these areas on different device sizes and scenarios. In conjunction with the *comfortable areas* for BoD input [33], this enables designers to design BoD input controls which consider unintended inputs and reachability in single-handed grips.

In this paper, we use a quantitative approach to empirically study *supportive micro-movements* during common smartphone tasks and scenarios. While participants perform abstract touch gestures, read, and write text in a sitting and walking scenario on four different smartphones, we recorded the movement of all fingers with a high-precision motion capture system. Based on the motion captures, we identify the *grip areas* which represent all on-device areas in which *supportive micro-movements* occur (*i.e.*, touches on the device surface which could lead to unintended inputs) and analyze them in relation to the *comfortable area* [33]. As a result, we derive the *safe areas* which are ideal locations to place BoD input controls. *Safe areas* represent areas on the device surface which are within the *comfortable areas* but outside of

the *grip areas*. Input controls within this area are not touched due to *supportive micro-movements* but are still comfortably reachable in a single-handed grip. We further found that 5" devices induce the least unintended inputs and require the least perceived workload by users. We derive three design implications for BoD input controls which help designers to consider reachability and unintended inputs.

Our contribution is three-fold: For four different phones using a single-handed grip, we (1) describe *supportive micro-movements* and their properties, (2) derive three design implications for BoD input, and (3) a data set of labeled 3D finger joint motions for common tasks while sitting and walking.

2 BACKGROUND AND RELATED WORK

We analyze *supportive micro-movements* during common smartphone use and the generated unintended input to derive design implications for BoD input. Thus, we review previous work on mobile input beyond the touchscreen, finger movements and grip shifts during smartphone interaction, as well as approaches for rejecting unintended input.

Input beyond the Touchscreen on Mobile Devices

Recent trends in smartphone development indicate that touchscreens will not be the sole input control anymore. Secondary screens on the rear or foldable phones will enable a wide range of novel use cases. For instance, BoD input can be used to solve the fat-finger problem [59] as the touchscreen on the front cannot be occluded [3, 68]. Similarly, Yoo et al. [70] proposed using the index finger on the back to access targets which are not reachable by the thumb using a single-handed grip [4, 28, 33]. These techniques transfer input from the rear to the front touchscreen. Thereby, unintended inputs could lead to sensitive and detrimental errors. Even with less critical consequences (*e.g.*, shifting screen content [29] and BoD pressure as action modifiers [12]), accidental activations still frustrate users as shown in previous work [7]. This also applies to use cases such as 3D object manipulation [2, 57] with BoD input, as well as one-handed zooming [21] and document navigation [60] with input on the sides.

Beyond a direct translation of rear to front input, previous work presented approaches to interpret the hand grip for adaptive user interfaces. With recent functional prototypes of *fully touch sensitive smartphoiness* (FTSPs) which comprise capacitive sensing on the whole device surface [8, 31, 32, 34, 42, 43], researchers showcased the possibility of grip recognition for adaptive user interfaces [8, 10, 11, 17, 20], predicting future input [42, 46] and errors [43], as well as for action modifiers and finger-aware interactions [34]. Especially with finger-aware input, we need to understand general as well as finger-specific *supportive micro-movements* to design suitable BoD input controls.

Dependent Finger Movements of Mobile Touch Input

Although users intend to move only the thumb to perform single-handed input on a front touchscreen, they unconsciously perform a wide range of further “*dependent*” movements. These movements maintain the balance and grip on the device, increase the reachability of the thumb on the display (e.g., through tilting [9] and grip shifts [13, 14]), or are unavoidable due to the limited movement independence of fingers (e.g., moving one finger also moves other fingers [18]). An important basis to design BoD input controls that take unintended input into account is the analysis of *supportive micro-movements* during common smartphone tasks.

Tilting the device is one type of *supportive micro-movements* which is used to increase the thumb’s reachability on the display. Previous work found that users tilt the device towards their thumb to reach farther distanced targets (e.g., at the top left corner) and away from their thumb to reach targets at the bottom right corner [9, 14]. Eardley *et al.* [13–15] referred to all movements which increase the reachability as “grip shifts” and explored them for different device sizes and tasks. Based on video recordings with manually identified key points and accelerometer values, they quantified the number of grip shifts during common smartphone tasks. They found that more grip shifts occurred with increasing device sizes while the amount of tilt and rotation varied with grip types and phone sizes. Moreover, they showed that the body posture (e.g., sitting and standing) affects the device movements, suggesting that different device sizes and body postures need to be considered for exploring *supportive micro-movements*. While these findings explain the device movements, no previous work investigated the actual finger movements which could generate unintended input on the device surface.

The limited independence of finger movements causes another type of *supportive micro-movements*. Previous work in biomechanics found that even when asked to move just one finger, humans usually also produce motion in other fingers [18]. The limited independence of the fingers is due to biomechanical interconnections such as connected soft tissues [67] and motor units [54]. Moreover, Trudeau *et al.* [64] found that the thumb’s motor performance varies by the direction and device size during single-handed smartphone use while the motor performance is generally greater for two-handed grips [63].

Identifying Unintended Input

Previous work investigated techniques to reject unintended inputs especially on tablets during inking scenarios (i.e., palm rejection). Annett *et al.* [1] used a motion capture system to capture movements during inking scenarios on tablets and evaluated different approaches to reject unintended palm touches including hand models [62, 65, 66] and contact

areas [30, 44, 55]. This conforms with findings by Matero and Colley [41] who showed that region and duration are the most successful features to reject unintended palm touches on smartphones. *TouchShield* [25] applies rejection regions on touchscreens by ignoring all touch events around the touched areas. With a dwell time based activation, this approach enables users to use the thumb for holding the device while the BoD fingers perform input. Since fingers on the back mostly move within a consistent area when holding a smartphone due to anatomy, techniques similar to the ones for palm rejection could reject the majority of unintended inputs. Thus, an understanding of the *grip area* is vital for designing BoD input controls.

Summary

Previous work presented promising use cases based on input beyond the touchscreen. BoD and side input solve the limitations of touch input while they noticeably extend the input vocabulary. However, BoD is not widely adopted yet due to two main challenges: the reachability problem and unintended inputs. The reachability problem can be solved by placing input controls within the *comfortable areas* which previous work empirically determined [33]. However, without minimizing unintended inputs, detrimental errors could occur which frustrate users [7] and render all novel use cases and interaction techniques ineffective. Ideally, BoD input controls need to be placed so that they are reachable without a grip change but also in a way which minimizes unintended input. This requires an investigation of *supportive micro-movements*, their properties, as well as the areas in which they occur. The results would derive design implications to design BoD input controls which consider both the reachability (c.f. Le *et al.* [33]) as well as unintended inputs.

3 STUDY

We conducted a study to analyze *supportive micro-movements*. We focused on the size and position of *grip areas*, the amount of finger movements within, and the length of typical trajectories of *supportive micro-movements* on different smartphones to inform the design of BoD inputs. We adapted the approach by Le *et al.* [33] to find *comfortable areas* which are not covered by *grip areas*. Moreover, we assessed the perceived workload and usability for each smartphone to understand the effort caused by *supportive micro-movements* during single-handed input from the user’s perspective. We conducted the study in a sitting and walking scenario as previous work showed significant effects of walking (e.g. hand oscillations) on smartphone interaction [5, 15, 48].

We used a within-subjects design with SCENARIO and PHONE as independent variables. SCENARIO consists of *sitting* on a chair, and *walking* on a treadmill to simulate a mobile

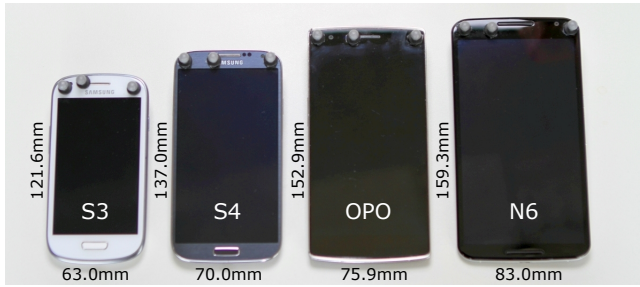


Figure 2: Smartphones used: Samsung Galaxy S3 Mini, Samsung Galaxy S4, OnePlus One, and Motorola Nexus 6.

scenario with hand oscillations and motion tracking capability. For each SCENARIO, we used four PHONE sizes. We alternated the order of the SCENARIO for each participant and counterbalanced PHONE with a Latin Square. In each condition, participants performed three tasks representing realistic use cases and in a randomized order: *reading* a text, *writing* messages, and performing *abstract input* gestures.

Apparatus

We used the same set of smartphones as Le *et al.* [33] which are shown in Figure 2. These devices were selected due to a steady increase in device width which influences the grip the most [29, 61]. From small to large, we used a Samsung Galaxy S3 mini (*S3*), Samsung Galaxy S4 (*S4*), OnePlus One (*OPO*), and a Motorola Nexus 6 (*N6*).

We used an *OptiTrack* motion capture system with eight cameras (*OptiTrack Prime 13W*, 240 *fps*) to record finger movements with sub-millimeter accuracy. The cameras were firmly mounted to an aluminum profile rack as shown in Figure 1. We attached 25 reflective markers (6.4 *mm* spherical markers) on all joints of the hand similar to previous work [16, 33] as shown in Figure 3. In addition, we attached four markers as a rigid body at the top of each smartphone for tracking it with six degrees of freedom (DoF) as shown in Figure 2. Participants were sitting on a chair without an armrest in the *sitting* SCENARIO and walked on a treadmill in the *walking* SCENARIO (see Figure 1). Participants walked with 3 *km/h* which is the preferred walking speed during the interaction with mobile devices [5].

We developed a custom application to replicate realistic writing and reading tasks which also enables us to log all events. Moreover, we adopted the tasks used by Le *et al.* [30] to cover common touch gestures and induce grip shifts. Our application instructs participants to perform different tasks and logs timestamps for each touch event so that we can synchronize them with *OptiTrack*'s motion data. Figure 4 shows screenshots of the respective tasks.

Tasks & Procedure

For each PHONE and SCENARIO, participants performed three tasks. In the *writing* task, participants transcribed excerpts of MacKenzie's phrase set [40] which simulates a text messaging application (see Figure 4a). In the *reading* task, participants read and scrolled through text passages for English learners [52] (see Figure 4b) for two minutes and answered three comprehension questions which motivated them to focus on reading. With an *abstract input* task, we cover common touch gestures while inducing grip shifts. The task consists of three gestures: *dragging*, in which participants dragged a tile into a target shape with both being randomly placed within a 2×3 grid across the whole screen (see Figure 4c); *tapping*, in which they touched a target appearing at a random location for one second; and *scrolling*, in which they scrolled vertical and horizontal bars into a target shape. Each gesture was repeated 12 times in a randomized order. After each task, participants filled in a NASA-TLX questionnaire [19] and answered five 7-point Likert scale questions to assess the perceived workload and usability for each smartphone.

After obtaining informed consent, we collected demographic data and measured the participants' hand size. We attached the skin adhesive markers on their right hand to enable motion tracking. We explained the tasks and asked the participants to perform them on trial to ensure that everything was fully understood. While they held the devices in a single-handed grip, we did not instruct them to use specific grips as this would influence the generalizability of the study. Moreover, for the *writing* task, we instructed them to type as if they would text friends instead of artificially being as precise as possible. Including briefing, optional breaks, and attaching markers, the study took around 90 minutes.



Figure 3: Placement of the reflective markers (6.4 mm spheres) on the right hand for enabling motion tracking.

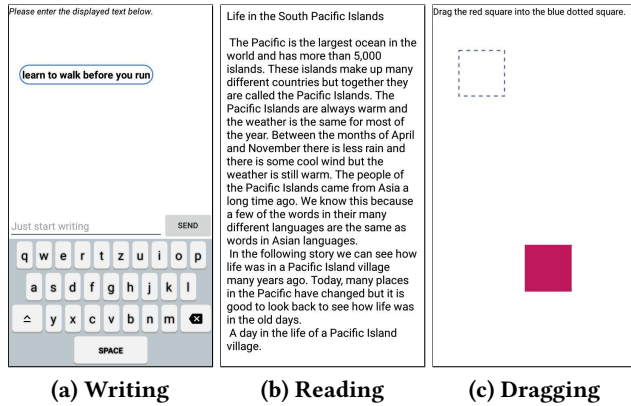


Figure 4: Application screenshots: (a) writing task, (b) reading task, and (c) abstract input tasks (here: dragging).

Participants

We recruited 16 participants (9 female, 7 male) between the ages of 18 and 27 ($M = 22.9$, $SD = 2.4$). All participants were right-handed. The average hand size was measured from the wrist crease to the middle fingertip and ranged from 17.5 cm to 22.0 cm ($M = 19.4$ cm, $SD = 1.4$ cm). Our collected data comprise samples from the 5th and 95th percentile of the anthropometric data [51]. Thus, the sample can be considered as representative. Participants were reimbursed with 10 EUR.

4 DATA PREPROCESSING

We preprocessed the 3D motion data into 2D heatmaps representing movements on the front and back side of the devices. To achieve comparability to the *comfortable areas* by Le *et al.* [33], we re-implemented their processing pipeline. In short, we applied the following preprocessing steps:

1. *Labeling Motions*: We labeled markers using semi-automatic labeling as provided by OptiTrack’s *Motive* software. To avoid marker swapping, we used a Max Spike of 4 mm/frame and a Max Gap of 5 frames. We did not use any reconstruction and smoothing approaches to avoid generating artificial marker positions. In total, we labeled 17,158,404 frames (*i.e.*, 19.9 hours of motion capturing).

2. *Transforming Global to Local Coordinate System*: We transformed each hand marker from the global coordinate system into the phone’s coordinate system and projected them onto the device surfaces. The pivot point is located at the top right corner on the front side. We validated the transformation by sampling five random frames per participant and manually checked them for correctness. While fingers in common grips (*i.e.*, in which the device’s rear faces the floor) touch the rear surface to balance and hold the device, rare cases could occur in which the fingers hover over the device’s rear

such as when holding the phone orthogonal to the floor. In contrast to rear touchscreens or finger painting, our approach enables to also consider finger movements which are slightly hovering during the study.

3. *Cleaning data*: We removed all frames in which the rigid body was not tracked due to occlusion or being out of the tracking grid. To avoid erroneous rigid body tracking (*e.g.*, marker swaps), we assumed that the phone was never held in uncommon orientations (*e.g.*, up-side-down, flipped). With this heuristics, we removed 2.1 % of all recorded frames.

4. *Generating 2D Heat Maps and Determining Grip Areas*: We generated 2D heat maps representing the *grip areas* with a raster size of 1×1 mm by projecting the markers onto the back and front plane. To remove noise caused by potential markers swaps, we removed all data points with a sum less than 10 in a 5×5 neighborhood (*i.e.*, all spots touched less than 41.6 ms at 240 fps). Using dilation and erosion on a binary version of the heat map, we then filled small gaps within the *grip areas*. The union of the binary heat maps of all participants and tasks finally represent the total *grip areas* per finger and device. In contrast to Le *et al.* [33], we did not remove outliers (*i.e.*, all spots not touched by at least 25 % of the participants) to cover all areas in which unintended inputs could occur instead of common *grip areas*.

5. *Determining Average Activity and Trajectory Lengths*: We represent the finger activity by their average movement speed in cm/s. Thereby, we calculated the movement speed between each subsequent frame and averaged them over all three tasks. We represent the average trajectory length in total travel distance (cm) of a BoD finger while the thumb moves towards the display and performs an input gesture. To determine start and end of single input trajectories, we used the timestamps of the *abstract input tasks* which are separated with short pauses in between. We removed noise caused by potential marker occlusions or swaps by filtering

Scenario	Finger	S3	S4	OPO	N6	Mean	SD
sitting	Thumb (F_0)	46.54	58.76	69.19	86.41	65.22	14.62
	Index (F_1)	14.43	17.23	23.12	26.82	20.4	4.86
	Middle (F_2)	12.67	15.1	19.28	22.62	17.42	3.82
	Ring (F_3)	7.4	13.88	15.96	20.15	14.35	4.6
	Little (F_4)	12.37	17.76	21.93	27.44	19.88	5.53
	\cup BoD (F_{1-4})	40.13	51.06	65.39	74.72	57.83	15.3
walking	Thumb (F_0)	50.01	60.92	68.79	88.26	67.0	13.97
	Index (F_1)	21.48	15.25	20.8	32.94	22.62	6.43
	Middle (F_2)	20.81	14.27	15.19	30.19	20.11	6.33
	Ring (F_3)	18.35	12.26	12.62	30.51	18.43	7.38
	Little (F_4)	21.88	18.05	22.39	41.09	25.85	8.96
	\cup BoD (F_{1-4})	61.13	51.48	62.4	101.05	69.02	21.91

Table 1: Grip areas in cm^2 for all fingers and scenarios on four devices. \cup BoD represents the union of the grip areas on the rear.

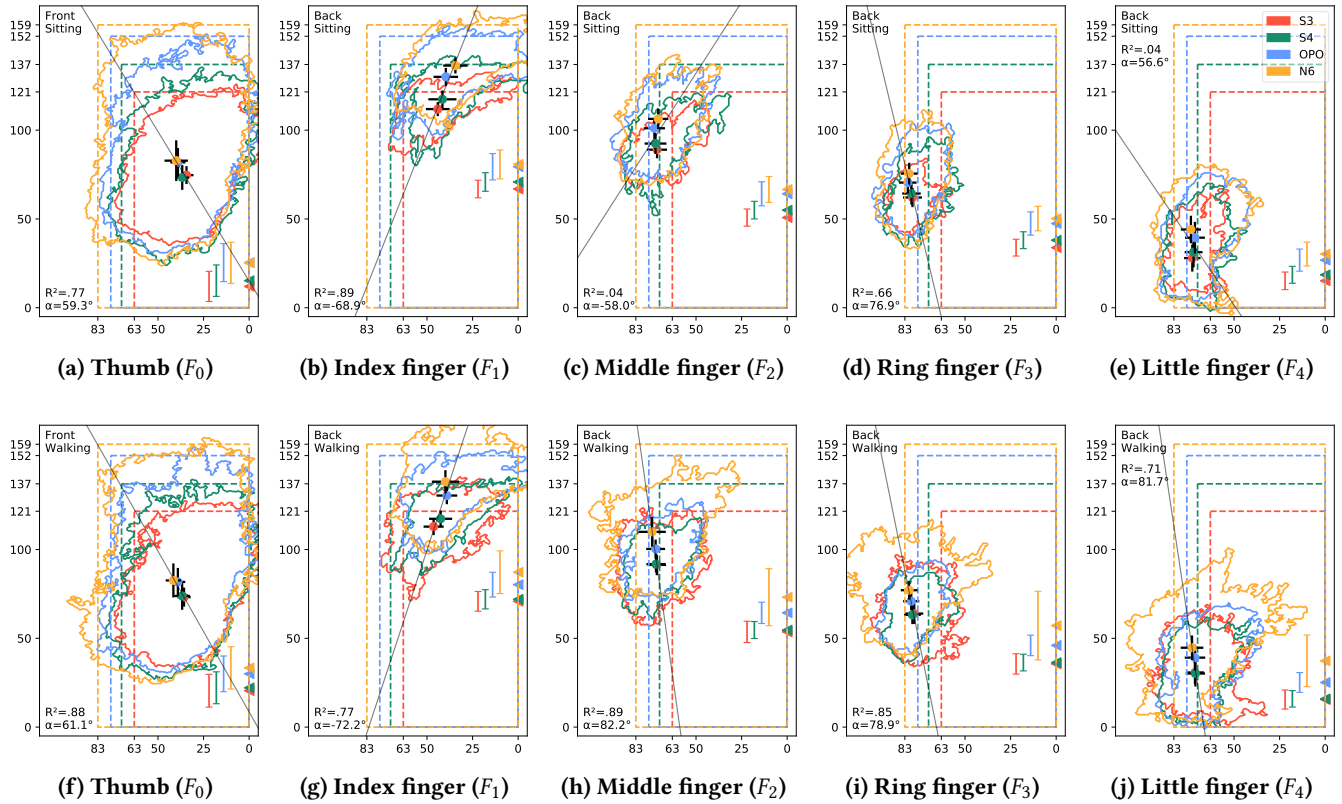


Figure 5: These figures show the grip areas for all fingers on four different devices (S3, S4, OPO, N6) and in two scenarios (SITTING, WALKING). Dots indicate the area’s centroid with whiskers indicating the standard deviation. Black lines visualize the areas’ shift with angle α towards the upper left corner with increasing device sizes. Triangles and lines on the right show the average y-position of the respective finger’s MCP joint and thus describing the grip. Device sizes are indicated by dashed lines and ticks in *mm*. Movements of the thumb took place on the front side while all other movements were on the back side.

the X and Y coordinates for outliers with a $M \pm 3SD$ filter. The filter removed 0.27% of the data.

5 RESULTS

We present the *grip areas*, finger movement activities, lengths of finger trajectories, and perceived workload and usability for each device. We abbreviate fingers with F_0 to F_4 (i.e., thumb to the little finger) and use square brackets to report values for all fingers [$F_0 F_1 F_2 F_3 F_4$] and devices [$S3 S4 OPO N6$]. We mapped the origin (0, 0) of all figures to the bottom right device corner as participants used their right hand. While we report the *grip areas* of the thumb for comparison, all ANOVAs are conducted without the thumb as a level for FINGER since we are focusing on unintended BoD inputs. All conducted Tukey post hoc tests are Bonferroni corrected. We corrected the DoFs using Greenhouse-Geisser in case the assumption of sphericity had been violated.

Grip Areas

Figure 5 shows the grip areas for all fingers and devices in the *sitting* and *walking* scenario across all three tasks. The colors of the contours represent the device, and the dashed lines represent the size of the respective device. In the following, we describe the characteristics of these areas.

Area Size. Table 1 shows the size of the *grip areas* for each finger, PHONE, and SCENARIO in cm^2 . A Pearson’s correlation test revealed significant correlations between the device’s diagonal length and the size of the *grip area* in the *sitting* SCENARIO for all fingers ($r = [.971 .983 .983 .977 .986]$, $p = [.029 .017 .017 .022 .014]$). This correlation can be described as a linear behavior with an average fitness of $R^2 = [.94 .97 .97 .95 .97]$. For the *walking* SCENARIO, we could not find significant correlations between the device’s diagonal length and the size of the *grip area* for all fingers ($r = [.947 .605 .398 .445 .685]$, $p = [.053 .395 .602 .555 .315]$).

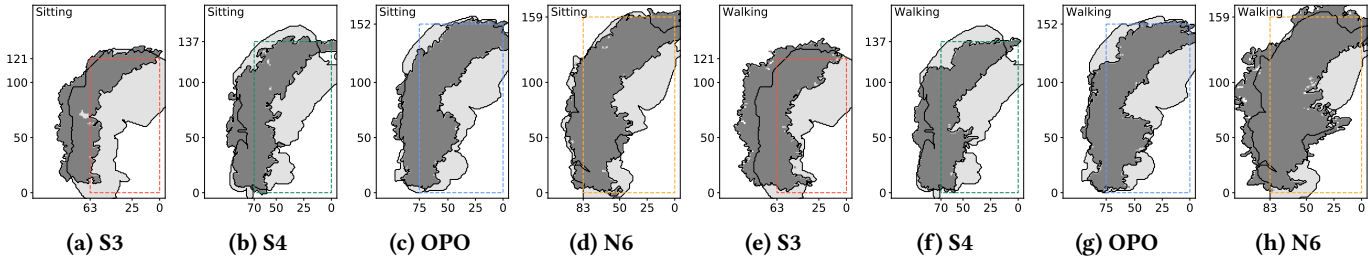


Figure 6: The dark gray areas represent the union of the back fingers' *grip area* ($F_1 - F_4$). The areas in light gray show the *comfortable areas* for the BoD fingers as reported by Le *et al.* [33]. We refer to the subsets of the *comfortable areas*, which are not covered by the *grip area*, as the *safe areas*. The axes denote *mm* starting from the bottom right corner.

A three-way RM-ANOVA revealed significant main effects for FINGER ($F_{2.60,38.95} = 4.41, p = .012$), PHONE ($F_{1.29,19.31} = 6.404, p = .015$), and SCENARIO ($F_{1,15} = .7.02, p = .018$) on the *grip area*. We found neither significant two-way interactions nor three-way interactions between the factors ($p > .05$, each). Tukey post hoc tests revealed sig. differences between OPO and N6 ($p = .036$) and S4 and N6 ($p = .007$). A further Tukey post hoc test did not reveal sig. differences between fingers.

Due to significant main effects of SCENARIO, we conducted two further two-way RM-ANOVAs on the *sitting* and *walking* subset. For the *sitting* SCENARIO, we found significant main effects for PHONE ($F_{3,45} = 9.26, p < .001$) but not for FINGER ($F_{3,45} = 4.41, p = .153$) and no two-way interactions between FINGER \times PHONE ($F_{2.95,44.19} = .616, p < .605$). A Tukey post hoc test revealed significant differences between the S3 and N6, between S4 and N6, and between the OPO and N6 ($p < .001$, each) but not for the other combinations ($p > .05$). For the *walking* SCENARIO, we found main effects for FINGER ($F_{1.89,28.30} = 3.83, p = .002$), PHONE ($F_{1.16,17.37} = 3.97, p < .001$), and a two-way interaction effect between FINGER \times PHONE ($F_{2.84,42.6} = 2.18, p = .003$). A Tukey post hoc test revealed significant differences between the S3 and N6, between S4 and N6, and between the OPO and N6 ($p < .001$, each) but not for the other combinations ($p > .05$).

Area Position. The dots in Figure 5 represent the area's centroid averaged over all participants and whiskers the SD.

For the *sitting* SCENARIO, the shift of the centroids towards the upper side can be described by a linear function with a fitness of $R^2 = [.77 .89 .04 .66 .04]$ for all five fingers. Pearson's correlation test revealed no correlation between the device's diagonal and a gradual shift of all fingers towards the top left corner ($r = [.877 -.945 -.187 .811 .194]$, $p = [.123 .055 .813 .189 .806]$). For walking this shift can be described by a linear function with a fitness of $R^2 = [.88 .77 .89 .85 .71]$ for all five fingers. Pearson's correlation test revealed no correlation between the device's diagonal

and a gradual shift of all fingers towards the top left corner ($r = [.94 -.875 .942 .921 .841]$, $p = [.806 .06 .125 .058 .079]$).

Safe Areas. The dark gray areas in Figure 6 represent the total *grip area* on the back of the device. The light gray areas represent the total *comfortable area* as reported by Le *et al.* [33]. With both areas overlapping, the remaining light gray areas represent the area which is comfortably reachable while no *supportive micro-movements* occurred within these areas. We refer to these areas as the *safe areas*. The *safe areas* correspond to $[60.3 48.4 40.9 35.9]\%$ of the *comfortable area* during *sitting* and $[45.4 48.1 43.4 25.6]\%$ during *walking*.

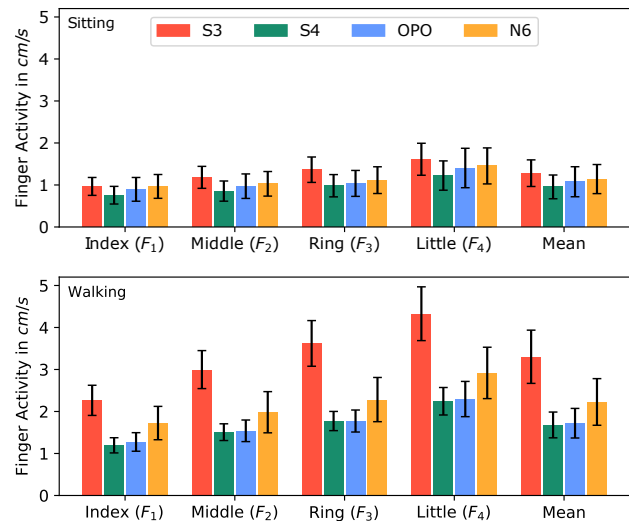


Figure 7: The average finger activity across all tasks in *cm/s*. Error bars represent the SD. We determined start and end of single input trajectories using the timestamps of the abstract input tasks.

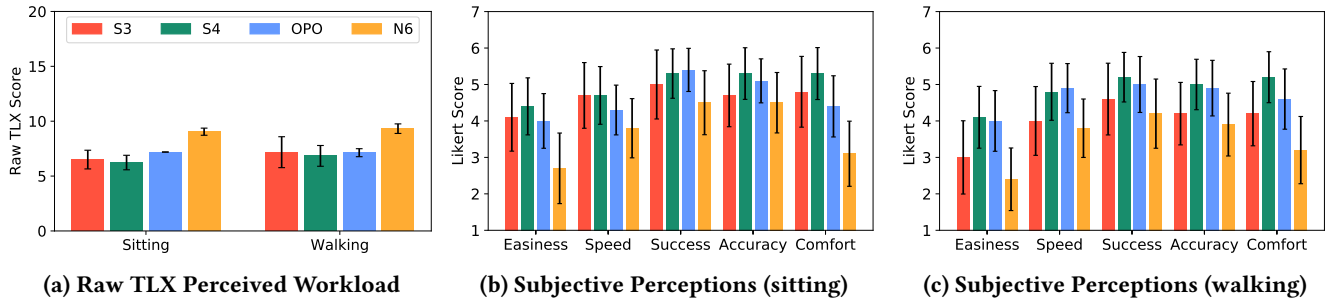


Figure 8: Perceived workload (unweighted NASA-TLX) and subjective perceptions of the usability (7-point Likert scale, *c.f.* Le *et al.* [30]) for each device averaged over all tasks. The colors represent the devices, attached whiskers the standard deviation.

Finger Movement Activity

Figure 7 depicts the movement activity of all fingers on all devices. A three-way RM-ANOVA revealed sig. main effects for FINGER ($F_{1,69,25.39} = 136.205, p < .001$), PHONE ($F_{3,45} = 46.25, p < .001$), SCENARIO ($F_{1,15} = 412.274, p < .001$), as well as for all two-way interactions ($p < .001$, each) and three-way interactions ($F_{3,33,49.99} = 9.45, p < .001$). Due to sig. main effects in SCENARIO, we conducted two further two-way RM-ANOVAs on the *sitting* and *walking* subset.

For the *sitting* SCENARIO, we found significant main effects for FINGER ($F_{1,69,25.39} = 54.67, p < .001$), PHONE ($F_{3,45} = 5.02, p < .001$), as well as a two-way interaction effect between FINGER \times PHONE ($F_{3,33,49.99} = 4.14, p < .001$). A Tukey post hoc test did not reveal any significant differences between the phones. For the *walking* SCENARIO, we found significant main effects for FINGER ($F_{1,79,25.90} = 176.35, p < .001$), PHONE ($F_{2,13,31.99} = 38.06, p < .001$), as well as a two-way interaction effect between FINGER \times PHONE ($F_{2,73,41.02} = 17.09, p < .001$). A Tukey post hoc test revealed significant differences between S3 and N6, S4 and N6 ($p < .05$, each), and between S3 and OPO and between S3 and S4 ($p < .001$, each).

Length of Finger Trajectories during Grip Shifts

Figure 9 depicts the 95th percentile for the length of finger trajectories as dots (left axis) and their means as crosses (right axis). A Pearson’s correlation test revealed significant correlations between the device’s diagonal length and the length of finger trajectories in the *sitting* SCENARIO ($r = [.957 .988 .969 .974 .997]$, $p = [.043 .012 .031 .026 .003]$) and for walking ($r = [.942 .981 .840 .868 .942]$, $p = [.058 .019 .160 .132 .058]$). The correlations can be described as a linear behavior with an average fitness of $R^2 = [.92 .98 .94 .95 .99]$ for *sitting* and $R^2 = [.89 .96 .71 .75 .89]$ for *walking*.

Perceived Effort between Phones

To evaluate the perceived workload and usability of each device averaged over all tasks, we used a raw TLX and 7-point Likert scale questions from previous work [30].

Perceived Workload. Figure 8a shows the average perceived workload measured with a raw NASA-TLX after each condition. A two-way ANOVA revealed significant main effects for PHONE ($F_{3,45} = 12.742, p < .001$) on the total workload but neither for SCENARIO ($F_{1,15} = 1.71, p = .21$) nor for two-way interactions between PHONE \times SCENARIO ($F_{3,45} = .429$,

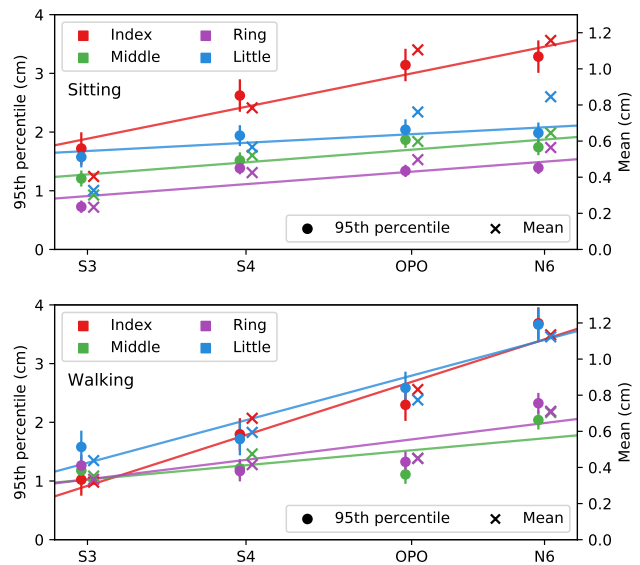


Figure 9: Length of finger trajectories in *cm* across the abstract input task. The dots (right axis) represent the 95th percentile and its linear growth (mean $R^2 = .75$). The crosses (right axis) represent the mean length.

$p = .733$). A Tukey post hoc test revealed sig. differences between N6 and OPO, N6 and S3, N6 and S4 ($p < .01$, each).

Subjective Perceptions. Figures 8b and 8c show the average perceived ratings when asked for easiness, speed, success, accuracy, and comfort after using a specific PHONE.

We conducted five two-way ANOVAs on the ratings on which we applied the Aligned Rank Transform (ART) procedure using the ARTool [69] to align and rank the data. For all ratings, the two-way ANOVAs revealed significant main effects for PHONE ($p < .05$, each). For the ratings easiness and accuracy, we found significant main effects for SCENARIO ($p < .05$, each). For easiness, we found significant two-way interactions between PHONE and SCENARIO ($p = .032$). Five corresponding Tukey post hoc tests revealed significant differences between S4 and N6 for all ratings ($p < .05$), between OPO and N6 for easiness, success, and comfort ($p < .05$), and between S3 and N6 for easiness and comfort ($p < .05$).

6 DISCUSSION

Previous work analyzed *comfortable areas* and presented design implications for BoD input controls to consider single-handed reachability. With our analysis, we identified suitable locations for BoD input, ideal device sizes, and further properties which help to minimize unintended inputs while maintaining reachability. We first discuss our results and then present three design implications for BoD input.

Safe Areas: Overlaps of Grip and Comfortable Areas

Safe areas are subsets of the *comfortable areas* in which no *supportive micro-movements* were observed. The *safe areas* cover 46% (43.5 cm^2) of the *comfortable areas* while sitting and 40% (38.4 cm^2) while walking on average. The majority of *safe areas* are located in the upper right quarter of the device and thus between the fingertips (when stretched) and the palm. Placing BoD input controls in these areas enable users to easily reach them by subtly flexing their finger. The fingertip of a flexed finger (see Figure 10a) provides enough force to activate a physical button (e.g., BoD volume buttons on the LG G-series) and suitable accuracy for touch-based input controls due to a small contact area. While finger parts (e.g., the *intermediate phalanges*) could come in contact with an BoD input control when stretched (see Figure 10b), the finger's force towards the device surface is too low (due to the force distribution) to hit the button's activation point. Even if users deliberately apply a force towards the back surface with a stretched finger, the center of pressure is located at the fingertip so that the phalanges cannot apply enough force to unintentionally hit a flat button's activation point.

For touch-based input, fingertips can be differentiated from phalanges by their contact areas. This is feasible with capacitive sensing which previous work used to identify

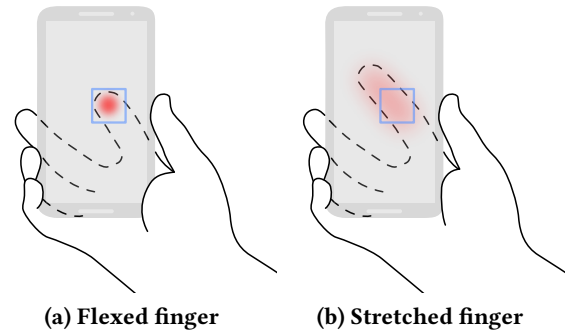


Figure 10: Performing input on a flat BoD button (blue square). The finger is flexed in (a) which leads to a small contact area. This bundles the force to hit the button's activation point (red dot). In (b), the finger is stretched, which leads to a larger contact area and thus a more distributed force which is not enough to activate the button (light red area).

touches of palms and other body parts on commodity devices [24, 30, 35, 36]. For fully touch sensitive smartphones, recent work presented a model to accurately translate contact areas on the device surface to the fingertips' 3D locations [34] which automatically omits touches by the phalanges.

Effect of Device Size on Grip Areas and Activities

We found the largest *grip areas* on the N6 in both sitting and walking scenario. For the sitting scenario, we further found a significant correlation between the size of the devices and *grip areas*. In contrast to the other devices, the unusually large size of the N6 requires additional *supportive micro-movements* to maintain a firm grip. The hand spans of our participants were not large enough to apply a firm grip which encompasses the whole device width (i.e., with a power grip [45]). More importantly, the 6'' touchscreen requires an extensive thumb range which can only be achieved with large grip shifts. An analysis of the finger trajectories lengths confirms that the larger grip shifts were indeed performed on the larger devices. This conforms with Eardley *et al.* [14] who found more device movements on larger phones.

Although the S3 entails a smaller *grip area* than the N6 as expected, we observed similar finger activities in a sitting scenario and significantly higher activities than on any other device in a walking scenario. The high finger activity on the S3 is due to a small touchscreen which requires *supportive micro-movements* for more input precision. As smaller contact areas lead to a more precise input [22, 23], additional *supportive micro-movements* were performed to enable the thumb to touch with a high pitch angle (i.e., nearly perpendicular to the display). Moreover, as the S3 fits well in the hand without a firm grip, users mostly held the device in a loose grip which provides the thumb with more flexibility.

In contrast, we observed the smallest *grip area* on the S4 while walking and on the S3 while sitting. Both the S4 and OPO are between the S3 and N6 in size and entailed less finger activity than the S3 (while walking) and the N6. Moreover, they do neither need additional *supportive micro-movements* for a firm grip nor to enhance the touch precision.

Effect of Walking on Grip Areas and Activities

We observed larger *grip areas* and significantly more BoD finger activity for walking than for sitting. Since walking introduces hand oscillations which previous work showed to affect mobile input [5, 49], additional *supportive micro-movements* are required to compensate the vibrations and avoid dropping the device. The hand oscillations also explain why there is no correlation between *grip area* and device size in a walking scenario as described above. The loose grip on the S3 provides the thumb with more flexibility, but also leads to more device movements in the hand caused by oscillations. Moreover, an analysis of the finger trajectories lengths reveals that the little finger moved significantly more in the walking condition. As the little finger stabilizes the grip from below, its movements indicate re-adjustments of the grips hampered by hand oscillations. These findings suggest that suitable device sizes are required to avoid *supportive micro-movements* for input precision and grip shifts. Thereby, we found that the size of the S4 is favorable for BoD input.

Perceived Usability and Workload

The perceived usability conforms to the observed finger movement activities. Especially for walking, we found a similar behavior to the finger movement activities in which the S4 and OPO are more favorable than other devices. Both devices received better ratings in easiness, speed, success, accuracy, and comfort which reflects the lower effort for holding and interacting with the devices. For the sitting condition, the N6 received the lowest ratings while the other devices received comparable ratings. This further highlights that the size of an S3 might be suitable for a sitting scenario but not under the influence of hand oscillations while users are walking. Results of the raw TLX revealed significantly more perceived workload on the N6 than on any other device. Again, we argue that this is due to its unusual size which even surpasses large versions of recent devices (e.g., iPhone XS Max).

Design Implications

We derive three design implications for single-handed BoD input. In conjunction with Le *et al.* [33], we inform the design of BoD input to consider reachability and unintended inputs.

Place BoD input controls within the safe area. Le *et al.* suggested placing BoD input controls within the *comfortable areas*

to avoid grip shifts. *Safe areas* are a subset of the *comfortable areas* in which no *supportive micro-movements* occurred. These areas are located in the upper right quarter of the device and are reachable by subtly flexing the index finger, which is also the most suitable finger for BoD input [33]. To avoid unintended input by other finger parts (e.g., *intermediate phalanges*), physical flat buttons should be used. Touch-based controls can use the contact surface or a contact translation model [34] to omit touches by other finger parts.

Consider 5" devices for single-handed BoD inputs. Large devices (e.g., Nexus 6) do not enable firm grips due to their width while small devices (e.g., Samsung Galaxy S3 mini) require a nearly perpendicular thumb and thus additional *supportive micro-movements* for input precision. We found that 5" devices (e.g., Samsung Galaxy S4) were perceived as the most usable while entailing the lowest amount of *supportive micro-movements* for single-handed use while sitting and walking. Thus, we recommend 5" devices for BoD inputs which represents a large fraction of current commercial devices. While BoD interaction can be used to solve reachability challenges, we believe that BoD input is, even more, promising for action modifiers and mode switches. Reachability challenges can be addressed by revising the GUI but usable efficient modifiers and mode switching remains a fundamental challenge.

Expect longer finger trajectories on larger devices. With increasing touchscreen sizes, larger grip shifts are required to provide the thumb with sufficient reachability. Thus, users perform a longer trajectory of *supportive micro-movements* (e.g., unintended stroke gesture) while shifting the grip. While the input trajectory length is a common feature to filter unintended inputs [41, 55], we recommend considering the device size when choosing the threshold. Figure 9 suggests threshold values in *cm* observed during grip shifts.

7 LIMITATIONS

To derive *safe areas* from *comfortable areas*, we focused on single-handed input from right-handed participants who held smartphones in their dominant hand. Future work could investigate the differences between left and right-handed users. We focused on generalizable design implications for everyday devices and thus prioritized realistic user behavior. Since smartphones are not produced for specific hand sizes and grips, we did not include the hand size as independent variable or controlled for the grip. Instructing grips would further limit the DoFs which leads to artificial behavior and unrealistic *grip areas*. As smartphones can recognize different grips with machine learning [6, 38, 39], future work could apply hand-dependent safe areas using our shared pipeline.

8 CONCLUSION & FUTURE WORK

We analyzed *supportive micro-movements* for BoD interaction during single-handed smartphone use. Our results help to avoid unintended inputs which frustrate users and lead to input errors. We identified *safe areas* in which we observed no unintended inputs and are reachable without grip shifts, found that 5" devices are the most suitable for BoD input, and proposed thresholds for trajectory lengths to filter unintended inputs. In conjunction with findings by Le *et al.* [33], our results help designing BoD input controls to consider reachability as well as unintended inputs.

One outcome of this work is a data set of labeled 3D finger movements recorded while users perform common tasks on four different smartphones while sitting and walking. We share this data set with the community to enable future work to investigate finger movements for specific properties such as hand sizes or grips. Moreover, the data set enables a better understanding of the hand while it interacts with smartphones, and could be used to study the *safe areas* in more detail. One interesting aspect is to compare them with the *comfortable areas* in terms of input performance. This helps to understand the trade-off between minimizing unintended inputs as well as the effort to move fingers during BoD input. Beyond understanding user behavior, our data set could also be used to train a machine learning model for fully touch sensitive smartphones that recognize unintended inputs.

9 DATASET

We release our data set (*i.e.*, motion captures and input events by the touchscreen) and the respective Python notebooks to preprocess the data and replicate our results: <https://github.com/interactionlab/unintended-input-dataset>.

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