Understanding How Mobile Interactions Shape Grasp and Contact Patterns Beyond the Touchscreen

Carolin Stellmacher
University of Bremen
Bremen, Germany
cstellma@uni-bremen.de

Leon Tristan Dratzidis
University of Bremen
Bremen, Germany
dratzidi@uni-bremen.de

André Zenner
Saarland University & DFKI
Saarbrücken, Germany
andre.zenner@uni-saarland.de

Iddo Yehoshua Wald
University of Bremen
Bremen, Germany
wald@uni-bremen.de

Johannes Schöning
University of St. Gallen
St. Gallen, Switzerland
Mohamed bin Zayed University of Artificial Intelligence
Abu Dhabi, United Arab Emirates
johannes.schoening@unisg.ch

Yvonne Rogers
University College London
UCL Interaction Center
London, United Kingdom
y.rogers@ucl.ac.uk

Donald Degraen
University of Canterbury
HIT Lab NZ
Christchurch, New Zealand
donald.degraen@canterbury.ac.nz

Mark Colley
University College London
UCL Interaction Centre
London, United Kingdom
m.colley@ucl.ac.uk

Figure 1: Exemplary contact maps of a smartphone held during Typing, Calling, and Gaming (left) and aggregated frequency maps across all participants (N=23) (right). Left-hand contacts are shown in pink and right-hand contacts in blue, with saturation indicating individual fingers, and the darkest tone marking the palm. Each subfigure depicts the smartphone's back plus its left, top, right, and bottom edges. Thermal imaging was used to capture heat signatures from the fingers and palms.

CHI '26, Barcelona, Spain

ACM ISBN 979-8-4007-2278-3/2026/04
https://doi.org/10.1145/3772318.3790565

Abstract

The way users hold a smartphone depends on the interaction task, yet little is known about the fingers' engagement with the device's surfaces beyond the touchscreen. Such an understanding not only opens up opportunities for novel on- and off-screen interactions, but also the device's possible physical affordances. We present a study (N=23) that examines the hands' physical engagement with the smartphone beyond the touchscreen across nine mobile interactions. Grasps were annotated from photographs, and contact regions were captured using residual heat traces from grasping the device. Our findings show that fingers and palms adopt a variety of support roles and postures when engaging with the smartphone's back and side edges. The hand-contact maps reveal distinct patterns, differing in contact frequency and placement. This work contributes an empirical characterisation of hands' back and edge engagement, highlighting design opportunities for future smartphone usage extending beyond the touchscreen.

CCS Concepts

• **Human-centered computing → Touch screens**; Empirical studies in interaction design; **Mobile phones**; Mobile devices; **Smartphones**.

Keywords

Grasp, Contact Pattern, Smartphone, Mobile Phone, Beyond the Touchscreen

ACM Reference Format:

Carolin Stellmacher, Leon Tristan Dratzidis, André Zenner, Iddo Yehoshua Wald, Johannes Schöning, Yvonne Rogers, Donald Degraen, and Mark Colley. 2026. Understanding How Mobile Interactions Shape Grasp and Contact Patterns Beyond the Touchscreen. In *Proceedings of the 2026 CHI Conference on Human Factors in Computing Systems (CHI '26), April 13–17, 2026, Barcelona, Spain.* ACM, New York, NY, USA, 20 pages. https://doi.org/10.1145/3772318.3790565

1 Introduction

Smartphones are central to everyday digital interaction and rely on continuous handheld operation, unlike stationary laptops or wrist-worn fitness trackers and smartwatches. This places multiple, simultaneous demands on the hands' physical engagement to facilitate precise touch input [11, 33, 53], avoid unintentional contact with the screen [44], stabilise the device while physically encumbered [48, 49], while minimising the risk of accidental drops. These demands are further shaped by the portable nature, as smartphones are used across dynamic contexts, including walking [50], running [57], or while being in the car [47]. Even without active interaction, smartphones are often held in the hand, affecting multitasking [51], highlighting the persistent embodied dimension of smartphone use throughout the day.

To better understand embodied aspects of smartphone use, prior work has examined device stabilisation [40], postural coordination [20, 27], or micro-movements that improve reachability [18]. Other works explored how supporting fingers perform device motion gestures and actively contribute to the interaction [75] or back-of-device (BoD) techniques, including finger gestures [60], pressure-based input [15], or characterisation of finger range of motion [35]. Despite these advances, we still lack a detailed account of (1) smartphone grasps and how the supporting fingers adapt their posture and engagement across interaction tasks and (2) contact points, describing where the users' fingers actually contact the device beyond the touchscreen. This research gap suffers from methodological challenges of visual occlusion, which hides the contact points with the device behind bent or overlapping fingers during the interaction. This renders external sensors insufficient and demands complex and expensive sensing hardware augmenting the device's surface to capture touch through pressure arrays [32] or capacitive technology [21, 52]. As a result, prior research has largely relied on ethnographic observations, limiting grasp characterisation to high-level one- or two-handed variants [39] and preventing capture of detailed contact points. Mapping accurate hand-device contact remains challenging, with existing approaches relying on projected 3D tracking data [35] or 2D visual mapping of fingertips [38]. A more precise account of hand-device engagement could reveal design opportunities that support touchscreen interaction alongside grasp and contact patterns, while accommodating broader physical demands of everyday smartphone use.

This paper deepens the understanding of how users' hands interact with smartphones beyond the touchscreen by addressing: (RQ1) How do users' fingers and palms engage with the smartphone beyond the touchscreen? and (RQ2) Where do users' fingers and palms contact the smartphone beyond the touchscreen? We conducted a user study with 23 participants performing nine everyday mobile tasks. Grasp configurations were analysed from multi-view video frames, and hand–device contact areas were captured via thermal imaging of residual heat. We found that fingers and palms adopted different support roles and postures, adjusting the grasp to accommodate touch input. The labelled contact maps reveal task-specific patterns in contact frequency and finger–side engagement, extending prior work [35, 38]. Joint analysis on grasps and contact areas provides a multi-faceted view of how fingers interact with the back and edge surfaces.

Contribution Statement:

The contribution of this work is threefold. First, we contribute an empirical understanding of hand-smartphone grasp configurations and contact patterns on the smartphone's back and side edges for nine interaction tasks. Second, we contribute a dataset[1], consisting of 1023 labelled thermal images (23 participants x 9 interaction tasks x 5 smartphone sides) depicting hand-smartphone contact regions through residual heat traces. Third, we extended an existing technique for grasp detection of non-digital objects to an electronic device and discussed the benefits and constraints for capturing contact regions via heat traces. The combination of grasp characterisation and contact patterns provides a multi-angled view into how users' hands physically engage with the smartphone, opening up opportunities for novel multimodal interactions on- and off-screen.

2 Related Work

In this paper, we examine how the hand supports, stabilises, and engages with the back and side edges of a smartphone across diverse interaction tasks, addressing a gap in understanding interactions beyond the touchscreen. By situating our study within existing research on smartphone grasps, hand placement and back-of-device interfaces, we demonstrate how patterns of grasp and contact complement prior work.

[1]The dataset is enclosed in the supplementary material and publicly available on GitHub https://github.com/CarolinStellmacher/Datatset-of-Grasp-and-Contact-Patterns-Across-Mobile-Interactions.git

2.1 Physical Interaction Between Hands and Smartphone

Work on the physical relationship between hands and smartphones has largely centred on grasp types and the small adaptive movements that occur during use. While grasp taxonomies are well established for general objects, smartphone-specific classifications remain sparse. Ahn et al. [3], for instance, extend an object grasp taxonomy by including only a single smartphone grasp, underscoring the lack of systematic coverage for mobile devices. Beyond such static classifications, studies show that users fluidly adapt how they hold devices to suit form factors and input modalities. When interacting via touchscreen rather than physical keyboards or styli, people tilt and rotate the device to improve reachability, with these micro-adjustments increasing as screen size grows [17, 18]. Prior ergonomics work shows that prolonged smartphone use and poor posture can lead to hand pain [6], highlighting the need to understand how handling distributes physical load. Body posture further modulates stability and movement. Hand adjustments intensify from standing to sitting to lying down [20], and lying on one's side yields the most secure, least mobile grip [27]. Related work on microgestures performed while holding an object reinforces that the hand rarely remains static during interaction [59]. Most prior work stops at broad grasp categories or general descriptions of small hand adjustments. Because individual fingers are hard to see and measure on a phone, we still lack task-dependent models of per-finger configurations; our study targets this gap.

2.2 Contact Patterns Between Hands and Smartphones

Complementary to grasp dynamics, several studies examine where and how the hand comes into contact with the device. Early work by Kim et al. [30] explored back-of-device grip patterns using painted gloves to detect hand positioning. Le et al. [38] mapped rear contact with heatmaps and reported that only a small fraction of the back surface is typically touched, with the index and middle fingers commonly contacting the centre, the ring and little fingers supporting the lower third, and the lower palm contributing a substantial number of touches. Lee et al. [39] further showed how task type, device width, and hand length shape grasp, reach zones, discomfort, and muscle activation during rear interaction. Studies of comfortable reachable areas for one-handed back-of-device interaction indicate that the index and middle fingers are particularly suited for BoD input in static portrait use [35], and PalmTouch demonstrates that the palm can serve as an additional, purposeful input modality [34]. Recent work identifies accidental back touches during one-handed use, outlining safe regions and noting the fewest incidents on 5" devices [37, 76]. Despite these insights, much of this literature isolates specific scenarios (e.g., static one-handed posture [35]), focuses on a single finger [77], or considers only a narrow set of mobile interactions [38]. Moreover, prior work concentrates primarily on the flat back of the device, leaving edges, which frequently contribute to support and stabilisation, underexplored. Research on BoD input systems provides additional clues about natural resting positions and movements of fingers and palm (e.g., see-through or pressure-augmented techniques) [13, 15, 36, 60, 72], as well as on-case and on-surface sensing with commodity phone sensors [79], yet these efforts primarily target novel input rather than documenting contact patterns. Consequently, comprehensive accounts of how full-hand contact varies across activities and grip variations, and how these contacts influence device support, are still lacking.

2.3 Detecting Grips and Contact

Touching and manipulating objects underpins most interactions, but because hand–device contact is largely hidden, external sensors struggle to capture it in detail. Consequently, grip detection has been extensively studied, with numerous real-time and offline solutions for general objects and, in particular, smartphones.

One approach is to sense the device itself, using overlays such as pressure arrays [32], or capacitive sensing [21, 52]. A second approach leverages built-in sensors, combining touchscreen, inertial data, and vibration to classify hand posture and grip pressure [23]. More recent work utilises front-facing camera corneal reflections to detect grip with ~85% accuracy and no extra hardware [81]. A third approach moves sensing to the hand via sensor gloves [65]. Finally, external-camera sensing has relied on patterned smartphone cases [38], or ML-based recognition of grasp postures [31].

While a variety of methods investigated these approaches, a few specific techniques were more widely utilised also for experiments, or for creating databases of object grasping information, showing reliability and empirical validation. A common method used for grasp detection is motion tracking. OptiTrack systems are often employed for capturing small finger movement [35, 58], or for capturing posture on top of just the grasp, as was done for the GRAB dataset [67]. Motion tracking using IMUs in combination with depth and standard video cameras was also used for creating a richer dataset [55]. Using motion capture (MoCap) is convenient for comprehensive, diverse datasets as it provides spatially accurate data and supports automated extrapolation. However, these advantages come at the cost of expensive equipment, complex physical setups, and substantial analysis pipelines. In addition, contact points on the flat surface of the device are only approximated, reducing accuracy. Another method with a similar balance to motion tracking uses EMG signals and machine learning to classify grasp types, originally for prosthetics [5] and later combined with sensors such as cameras [78]. In contrast, some studies, including on phones [14], use manual video coding, which is easy to set up but requires substantial manual effort.

For our study, we chose thermal imaging, which offers a simple setup while directly capturing contact areas rather than inferring them [68]. Although the images require manual encoding, they clearly visualise contact and are easy to interpret and integrate into digital workflows [25], which will become even more relevant as AI gradually offers more reliable and accessible image analysis tools. Our approach was particularly inspired by the ContactDB dataset, which used thermal imaging to create 3D contact meshes for household objects [9].

3 User Study

The goal of our user study was to examine how mobile interactions shape the way users hold a smartphone. To do so, we invited participants to perform nine common interaction tasks, during which we visually recorded their hand grips. Immediately after the task,

Table 1: Nine interaction tasks performed during the study.

Interaction Task	App Used in the Study
1. Scrolling (and reading)	News articles in mobile browser
2. Typing (a text message)	Google Chat
3. Calling	Google Meet
4. Gaming	Hill Climb 2 (Racing Game, landsc.)
5. Video	YouTube (Nature Video, landsc.)
6. Map	Google Maps
7. Volume	Physical side button
8. Photo (back camera)	Camera App
9. Selfie (front camera)	Camera App

we collected hand-smartphone contact by using a thermal camera, capturing heat traces transferred onto the smartphone's surface during use. Using this data, we investigated their (1) grasp and (2) contact patterns to derive insights on how the hands physically engage with the smartphone beyond the touchscreen.

3.1 Selection of Interaction Tasks

We applied a two-step process to select realistic, representative smartphone interactions for our study. First, we collected common use cases from literature, considering global smartphone usage [62], commonly used apps [12], and their generational differences [4, 10], as well as use contexts [71]. From this, we identified "Social Media", "Info Search", "Reading", "Messaging", "Calling", "Gaming", "Watching a Video", "Map Navigation", "Listening to Audio", and "Taking a Photo" as central use cases for our study.

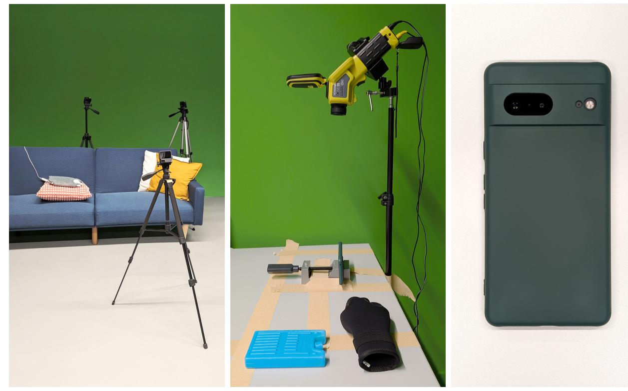
Secondly, we mapped these use cases to interaction tasks. "Social Media", "Info Search", and "Reading" were grouped into a single task, "Scrolling", as they all primarily involve scrolling and reading. Notably, this interaction task does not induce rapid grasp changes, unlike menu navigation or button presses, which was important for reliably capturing residual-heat contact areas.

We added two tasks for taking a photo, "Photo" and "Selfie", to distinguish between back- and front-camera use. For audio listening, which involves minimal direct contact, we used changing the volume via the physical side button, represented by the task "Volume", to ensure measurable contact. The final set of interaction tasks (see Table 1) was chosen to elicit natural grasp variations across device orientations, hand use, and on-body locations (e.g., held to the ear for calls), reflecting everyday smartphone use.

3.2 Design & Measurements

The study employed a within-subject design with all participants performing the same set of nine mobile interaction tasks (independent variable; summarised in Table 1). The interaction tasks were presented in random order, with short breaks of 1-2 minutes. As we were interested in how users hold the smartphone, we collected two main measures (dependent variables): grasps and hand-smartphone contact areas. Additionally, we measured participants' hand sizes and collected information on their demographic backgrounds and smartphone usage.

3.2.1 Hand Size & Handedness. At the beginning of the study, we used a measuring tape to assess the distance from the wrist crease (proximal end) to the tip of the middle finger of both hands, a common measurement for hand size in HCI [9, 35]. In addition, we recorded participants' self-reported dominant hand.



(a) (b) (c)

Figure 2: Setup and materials used in our user study: (a) Sitting arrangement with couch, pillows, three GoPro cameras with tripods and a heating pad with which participants warmed up their hands during tasks. (b) Set up to capture the heat residue left on the smartphone, comprising a thermal camera, a clamp to hold the smartphone, a neoprene insulating glove, and a cool pad to remove the thermal traces for the next task. (c) The Google Pixel 7 with a silicon case.

3.2.2 Hand Grasps. Video recordings of three GoPro cameras from three perspectives (front-facing and two overhead views on the left and right sides) captured participants' hands holding the smartphone during the interaction tasks. Static images of the grasps, extracted from these videos, were later used for analysis.

3.2.3 Hand-Device Contact. Consistent with previous research on objects with varying geometries [9], a thermal camera was used to record heat maps of the back and four sides of the smartphone immediately after each task. These recordings captured the residual heat transferred from the participant's hand to the device during the interaction. Because the participant's hands covered the device's surface during use, heat maps could not be derived in real time and were, therefore, obtained only post hoc.

For sufficient and reliable heat transfer and retention, we took multiple measures: participants warmed both hands for 1-2 minutes prior to each task using a 60 °C heating pad, and continued the interaction task and grasp for 30 seconds. Warming participants' hands also ensured dexterity comparability and removed any confounding factor caused by the variance in hand temperature. We used the same smartphone for all participants to keep surface and thermal properties consistent. For the study, the thermal camera recording the heat residue on the smartphone was calibrated to capture temperatures ranging from 25 °C to 37 °C, covering the average temperature range across the human hand of 27.0 to 33.4 °C [70]. The ambient temperature of the temperature-controlled study room remained at a constant 21 °C.

Table 2: Percentage of the employed smartphone orientation and the number and type of hands used to support the device during the interaction task, across all participants (N=23). Additionally, absolute numbers for one-handed support performed with the non-dominant hand are presented. Here, values are a subset of the corresponding one-handed support proportion.

	Portrait	Landscape	One-Handed Support	Two-Handed Support	One-Handed Support - Left	One-Handed Support - Right	Non-dom. Hand
Scrolling	100.0%	–	69.6% ($n = 16$)	30.4%	18.8%	81.3%	1 (6.3%)
Typing	100.0%	–	4.3% ($n = 1$)	95.7%	100.0%	–	1 (100%)
Calling	100.0%	–	100.0% ($n = 23$)	–	19.0%	81.0%	2 (9.5%)
Gaming	–	100.0%	–	100.0%	–	–	–
Video	–	100.0%	8.7% ($n = 2$)	91.3%	50.0%	50.0%	1 (50%)
Map	100.0%	–	56.5% ($n = 13$)	43.5%	76.9%	23.1%	6 (46.2%)
Volume	100.0%	–	87.0% ($n = 20$)	13.0%	10.0%	90.0%	0
Photo	43.5%	56.5%	13.0% ($n = 3$)	87.0%	–	100.0%	0
Selfie	100.0%	–	82.6% ($n = 19$)	17.4%	22.2%	77.8%	2 (11.1%)

3.2.4 Demographic Information and Smartphone Usage. At the end of the study, participants completed a questionnaire, assessing demographic information, smartphone usage, and experience.

3.3 Apparatus

All participants used the Google Pixel 7 (155.6 mm × 73.2 mm × 8.7 mm, 197 g, see Figure 2c), fitted with a commercially available soft silicone case. Its dimensions and mass closely align with the most widely reported smartphone profiles worldwide (height 150–160 mm, weight 150–200 g), making it a representative of a typical contemporary smartphone[2]. Using a single smartphone and keeping the screen size and physical dimensions consistent, we were able to isolate the effects of different mobile interactions on grasps and contact areas while maintaining consistent heat-residue retention.

For collecting contact data, we used the Trotec IC 080 L thermal camera, which was mounted on a tripod, positioned overhead, facing down at a table (see Figure 2b). A clamp, fixed to the tabletop with tape and within the camera's field of view, held the smartphone upright to capture the heat traces along the side edges. The thermal camera's video feed was recorded via OBS Studio, which was running on a laptop connected to the camera via cable. We later extracted images from the videos for the heat map analysis.

3.4 Procedure

The study was reviewed by the ethics board of the University of St. Gallen and was exempt from a formal full review. We conducted the study in accordance with local ethical guidelines, and participants provided written consent after receiving a brief verbal explanation about the study's purpose, task, and data collection. Additionally, participants received a 10€ compensation.

After the initial introduction and consent collection, we recorded participants' hand sizes. Participants were then seated on a couch (see Figure 2 (a)), reflecting a comfortable and natural environment for smartphone usage. Participants briefly familiarised themselves with the experimental smartphone and its physical shape before returning the device and placing both hands inside the heating pad. The study conductor wore a neoprene insulating glove throughout the experiment to prevent direct skin contact when handling the device and to avoid unintentional heat transfer. Radiating body heat did not produce any heat traces.

For each task, the study conductor prepared the smartphone by launching the corresponding app (see Table 1) and removing residual heat traces visible through the thermal camera, using a standard cool pack. Participants were then informed about the upcoming task and instructed to hold the device as they would naturally do, to elicit intuitive grasps. To initiate the task, participants removed their hands from the heating pad and grasped the smartphone.

Participants were allowed to sit in any posture that felt most natural to them while using the smartphone. This design choice reflects our aim to observe how users intuitively hold and grasp their devices under realistic, everyday conditions. By not constraining seating posture, we were better able to capture grasp and contact patterns as they naturally occur, rather than imposing an artificial behaviour that may not generalise to real-world usage.

After each task, the study conductor retrieved the smartphone and brought it to the thermal camera setup right next to the couch (see Figure 2 (b)), where they captured the heat residue on all five sides, stabilising the phone in a clamp to record the edges. During this time, participants returned their hands to the heating pad. This procedure was repeated for all nine tasks and lasted ~25 minutes. The experiment concluded with a demographic questionnaire that participants completed on a laptop. The experiment lasted about 40 minutes in total (~8 min introduction & hand measurement, ~25 min tasks & thermal recording, ~7 min demographic questionnaire).

4 Findings

We present the findings from our qualitative inquiry and the results of our quantitative analysis. We report participants' demographics and smartphone use, and characterise hand grasps. Contact patterns are reported regarding hand-device and finger-phone-side contacts, contact frequency, and placement on smartphone sides.

4.1 Participants, Hand Sizes & Handedness

The study involved 23 participants (aged 23-36, $M = 29.0$, $SD = 3.5$, with $f = 12$ and $m = 11$). We recruited 24 participants, but excluded one data set due to a recording error. The majority of participants had used mobile devices (earlier mobile phones or smartphones)

[2]https://scientiamobile.com/the-importance-of-knowing-physical-device-dimensions

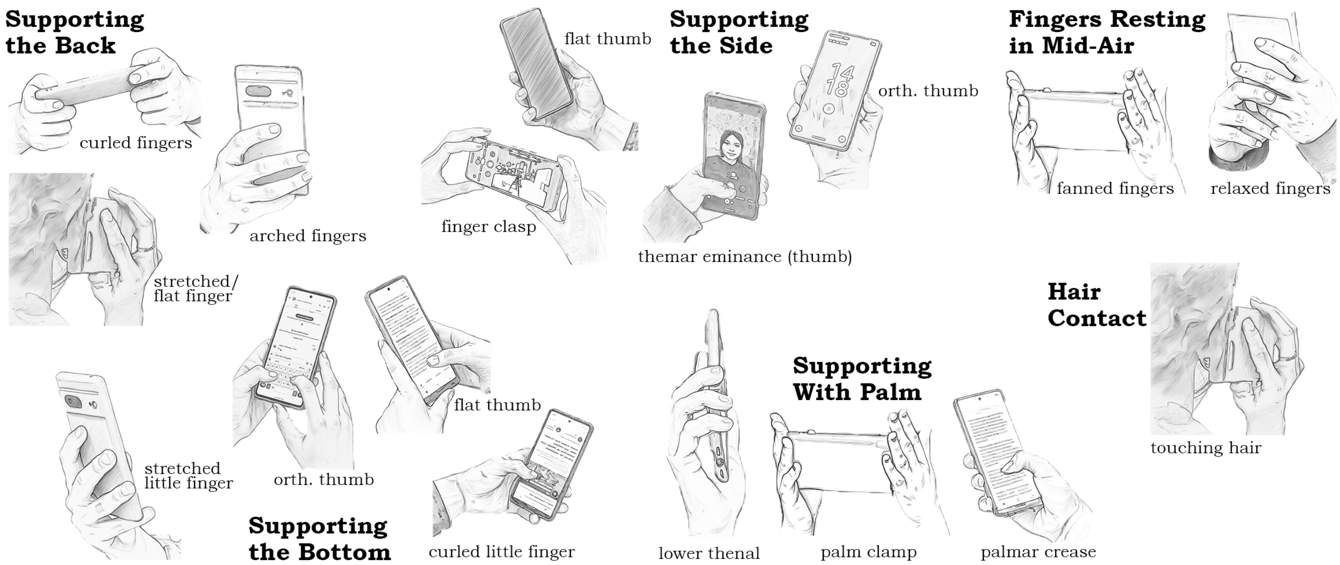


Figure 3: Grasp variations illustrating how fingers and palms supported and held the smartphone in our study.

for 16–20 years (56.5%), while smaller groups reported 11–15 years (30.4%) or 6–10 years (8.7%). Subjective self-rated experience with mobile phones was high (M = 4.2, SD = 0.7, min = 3, max = 5). Regarding smartphone cases they use on their personal smartphones, most participants reported using silicone (69.6%) or hard plastic (21.7%) cases, while one participant reported not using a case at all and another specified another type (vinyl sticker). When asked to indicate their three most common smartphone activities, participants most often selected messaging (73.9%) and social media (56.5%), followed by information search online (43.5%), listening to audio (30.4%), and taking photos (30.4%). Reading (21.7%), watching videos (21.7%), and map navigation (17.4%) were chosen less frequently, while calling (4.3%) and other activities such as online dating and gaming (8.7%) were rare.

Most participants were right-handed (n = 21; 91%), with two left-handed. The average right-hand size was M = 17.8 cm (SD = 1.3, min = 15.5, max = 22), while the average left-hand size was M = 17.4 cm (SD = 1.3, min = 15, max = 21.5). On the 5-item Likert scale "I held the phone during the study as I hold my own phone" (1=Strongly Disagree to 5=Strongly Agree), participants reported high agreement (M = 4.6, SD = 0.5). When asked why their grip might differ, participants most often pointed to differences in the size and shape of the device, but also mentioned the context of use (e.g., posture or task) and study-related effects (e.g., being filmed, leaving heat signatures).

4.2 Smartphone Grasps

We analysed 207 grasps (23 participants x 9 tasks) quantitatively and qualitatively to understand how hands physically engage with the smartphone across nine interactions (RQ1). For each grasp, we extracted static images from the GoPro videos capturing participants' hand postures. Posture characteristics were qualitatively analysed via an iterative open-coding procedure in line with Blandford et al. [8], using the MaxQDA data analysis software. Two authors performed an initial round of open coding on two data sets each, covering 17.39% of the overall data (4 out of 23). One author then completed the remaining data sets to characterise postures.

4.2.1 Quantitative Results of Smartphone Orientation, Support Grasps, and One-handed Support. Results are summarised in Table 2. Device orientation was kept consistent within each task, and almost all participants used the same orientation per task. Only the Photo task is split roughly evenly between portrait and landscape, reflecting natural variation in back-camera use. This freedom to choose their own grasp ensured that any measured effects of interaction on the device could be attributed to the task itself rather than variations in device handling.

Regarding the number of hands used to grasp the smartphone, Calling was consistently one-handed, and Gaming was consistently two-handed. The other tasks varied, but most exhibited a clear trend toward either one- or two-handed support, except Map, which was split between both. In most cases where the smartphone was supported only by one hand during the interaction, participants showed a clear tendency to use either their left or right hand. Cross-checking the supporting hand with reported handedness showed that using the non-dominant hand when using only one hand to support the device was less frequent. An exception was the Map interaction, in which nearly half of the one-handed support cases (6 (46.2%)) used the non-dominant hand to support while the dominant hand provided touch input.

4.2.2 Qualitative Findings on Finger Configurations. To understand how users' hands physically engage with the smartphone, we characterised the support roles adopted by the fingers and palm to stabilise a secure grasp while enabling touchscreen input and operation of side-mounted buttons.

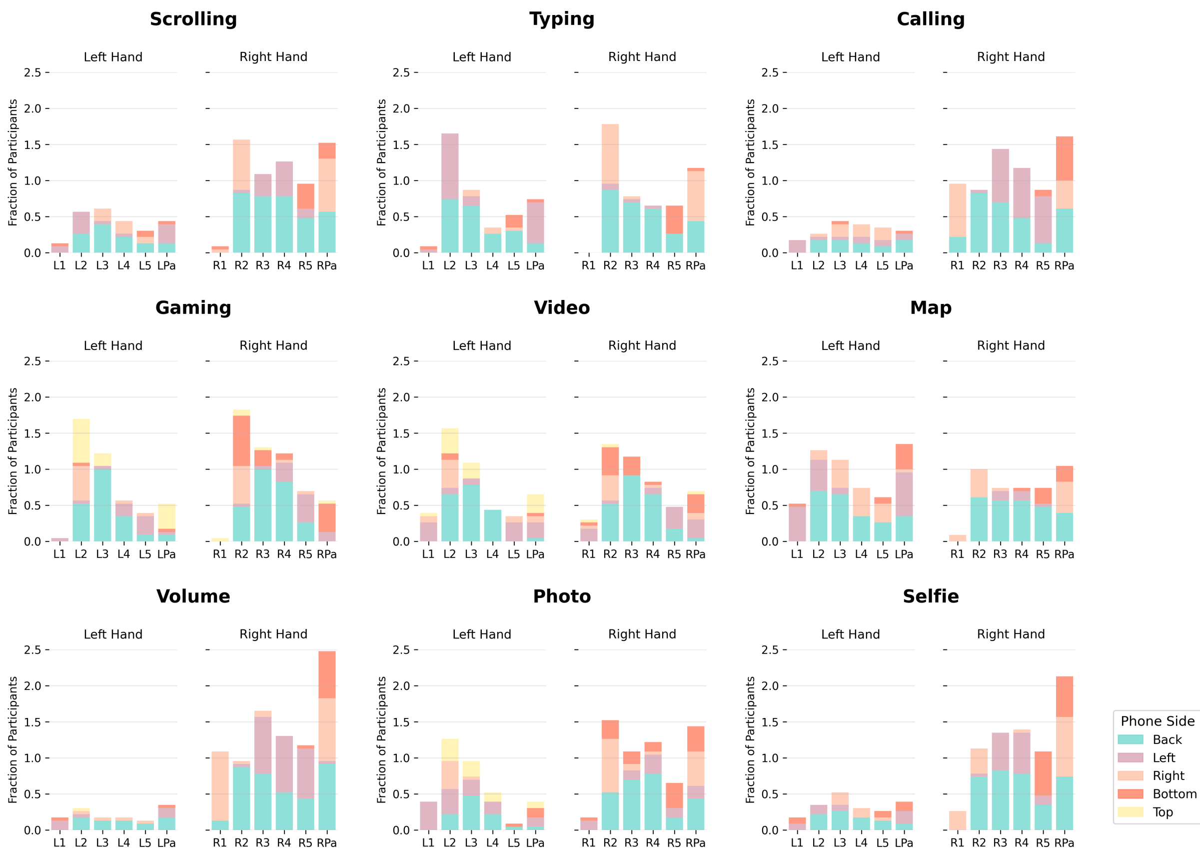


Figure 4: Fraction of participants placing their fingers or palm on the smartphone's back and side edges across tasks. R1–R5 is used for the Right Thumb–Little Finger, L1–L5 for the Left Thumb–Little Finger, and RPa/LPa for Right/Left Palm.

Table 3: Frequency of hand contact on the smartphone's back and four side edges across interaction tasks. Higher frequencies are encoded by stronger colour saturation.

	Back	Left	Right	Bottom	Top
Calling	41.9%	30.0%	19.2%	8.9%	0.0%
Gaming	45.7%	14.7%	11.6%	14.7%	13.4%
Map	49.3%	19.2%	21.8%	9.6%	0.0%
Photo	36.9%	21.3%	18.2%	15.1%	7.6%
Scrolling	51.0%	18.9%	21.4%	8.7%	0.0%
Selfie	46.0%	18.6%	19.5%	15.8%	0.0%
Typing	53.5%	19.7%	19.2%	7.5%	0.0%
Video	45.3%	19.2%	12.6%	12.1%	10.7%
Volume Up	43.7%	26.6%	21.4%	7.9%	0.4%
Mean	45.9	20.9	18.3	11.2	3.7
SD	4.98	3.32	4.64	3.73	5.44
MIN	36.9	7.5	14.7	11.6	0.0
MAX	53.5	15.8	30.0	21.8	13.4

Supporting Roles of Fingers and Palms. Findings are illustrated in Figure 3. Two prominent roles involved supporting the smartphone's back or bottom. For back support, we observed three patterns. First, participants placed a stretched index finger flat on the surface, typically near the centre or opposite edge, sometimes accompanied by the middle, ring, and little fingers. Second, fingers were curled on the back, which was most common in two-handed grasps, involving the index, middle, ring, and/or little fingers. In some cases, we observed the index, ring, or middle finger wrapping around the edge at their interphalangeal joints and contacting the back only with their upper segment/tip. In landscape mode, similar wraps occurred around the top corners. Third, arched fingers created a near-continuous contact along their length, forming a gentle bridge over the back surface. This occurred mainly in two-handed grasps and occasionally in one-handed grasps using the index or middle finger. Supporting the smartphone's bottom often involved the thumb or little finger in both one- and two-handed grasps. Participants varied this placement between a flat thumb along the bottom edge, a thumb oriented approximately orthogonally to the edge, and a curled or stretched little finger (e.g. Selfie or Calling) positioned diagonally across the edge.

Supporting the side edges depended strongly on the grasp type. In one-handed grasps, the device was typically pinched between the thumb on one side and the middle, ring, and little fingers wrapping around the opposite side. The thumb was placed either flat along the edge, flexed to contact with the tip, or the device rested on the thenar eminence (the mound at the base of the thumb). In two-handed grasps, the purpose of maintaining an upright device orientation was especially evident. In landscape orientation (e.g., Video), the thumb frequently supported the bottom edge while the index or middle finger stabilised the top edge or corners. In rare two-handed cases during Selfie and Photo, two participants placed a thumb on the slightly protruding front lip of the protective case to support the device while avoiding unintended touchscreen contact.

The way the palm supported the device differed from finger roles. The palm served more as a platform, with bottom edges and corners nested into the central palmar crease or the lower thenar region. In a symmetrical two-handed landscape grasp, the device was clamped between both palms with minimal finger contact.

Role of Wrist Support. We also observed that entire grasps stabilised the device at distinct tilt angles relative to the screen-normal (the vector orthogonal to the touchscreen), implying varying loads and contact pressures on the fingers. We categorised these angles as recline (0-45°), upwards (45-85°), forward (~90°), forward with rotation (~90° plus rotation), and downward (>90°). Recline was predominant, followed by upward and forward, and was observed multiple interaction tasks. During Calling, participants frequently adopted a forward-with-rotation posture to hold the device to the ear, producing a lateral weight shift and increased pressure on the supporting finger along the downward-facing side edge. Downward angles were rare and observed only when taking overhead Selfies.

Beyond Finger Support. In some grasps, certain fingers did not contribute to support at all as they were used for touch input or to press the side-mounted button. In two-handed grasps, the thumbs and index fingers commonly operated the screen. In one-handed grasps, the index finger and/or thumb handled both for touchscreen input and the side button. In one case, the middle finger was used to press the button. Some fingers rested in mid-air, mostly the little, ring, and occasionally the middle finger. These fingers were either comfortably flexed (often touching each other) or splayed like a fan while the remaining fingers clasped the device. During Video, thumbs also occasionally hovered above the screen. Such "surplus" fingers were not observed in one-handed grasps. We also observed instances where support extended beyond the hands. In one-handed Calling, the device was pressed against the ear and adjacent facial areas, with occasional additional contact from hair or spectacles.

4.3 Contact Patterns

To determine where participants' hands come in contact with the smartphone beyond the touchscreen (RQ2), we captured thermal images depicting temperature-based handprints from which we derived contact maps. To do so, we manually extracted frames of the smartphone's back and side edges from the thermal camera's video recording, yielding 1032 images. Three instances were missed during data collection (expected 1035 = 23 participants x 9 interaction tasks x 5 device sides), but visual inspection of the corresponding grasp photographs confirmed that no finger contact occurred on these surfaces. We registered and aligned images within each

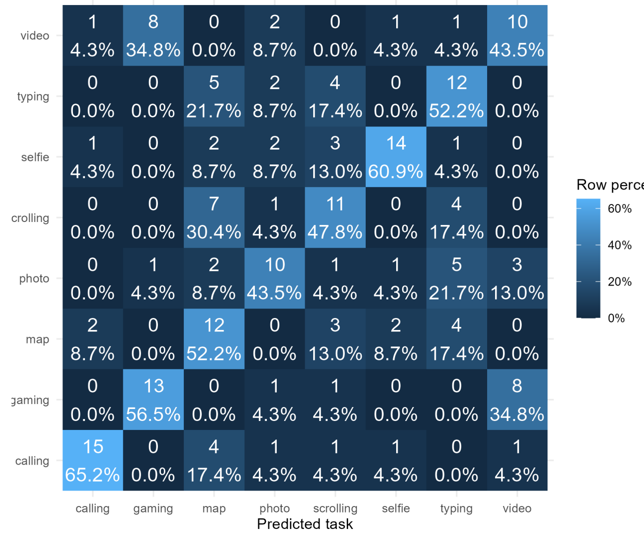


Figure 5: Confusion Matrix for predicting the task from the contact map.

smartphone-side set using standard image-processing techniques in Python. We then employed the Segment Anything Model 2 (SAM 2) [54] to automatically segment thermal handprints and pre-detect contact regions, which were stored as masks in an XML file. Finally, we imported the images and the corresponding XML mask files into the Computer Vision Annotation Tool (CVAT, https://www.cvat.ai/) to manually refine the masks and label them by finger type and palm, cross-referencing the multi-angle grasp photographs. Refinement involved removing wrongly detected masks that did not contain residual heat, creating missing masks, editing the shape of masks , and merging masks that had been incorrectly split. The supplementary material includes the full dataset of 1032 thermal images, their finger and palm annotations, contact maps per participant (see Figure 6), and accumulated contact maps per interaction task (see Figure 7). For compactness in this section, we use R1–R5 for the Right Thumb–Little Finger, L1–L5 for the Left Thumb–Little Finger, and RPa/LPa for Right/Left Palm.

4.3.1 Hand Contacts Beyond the Touchscreen. All smartphone sides experienced touch contact with the hands. The frequency of how often each smartphone side was touched across interactions is shown in Table 3. The Back surface accounted, on average, for nearly half of hand contacts. Both side edges exhibited lower frequencies, though similar to each other. By contrast, the Bottom and Top were contacted infrequently. Notably, no participant placed their hands on the smartphone's top edge during the six interactions Calling, Map, Scrolling, Selfie, Typing, and Volume change.

4.3.2 Finger Contacts Beyond the Touchscreen. To understand the role of each smartphone side for each interaction task, Figure 4 presents the proportion of participants placing each finger or palm on the back and side edges. Descriptive statistics are provided in the supplementary material.

Across tasks, the back contact dominated, particularly for the right hand. During Scrolling and Map, contacts from R2 to RPa were similarly frequent on the back, whereas Video and Calling showed greater variability in which fingers contacted the back. Multiple-side occurrences reflect either inter-participant diversity in grasp or simultaneous contact with several sides. In Selfie, the right palm often touches the Back, Right, and Bottom edges, consistent with cradling the bottom-right corner. For fingers, multi-sided occurrences suggest wrapping around the edges. Although the Top was rarely contacted in most tasks, it was more prominent in Gaming, Video, and Photo. Patterns of one- vs two-handed support were also evident as one-handed tasks (Scrolling, Calling, Volume, Selfie) showed minimal left-hand contact, whereas two-handed tasks displayed more balanced left–right engagement.

We also checked the statistical difference between the frequency of each side being used. As the data was non-normally distributed, we used the ARTool package Wobbrock et al. [73], applying the aligned rank transform procedure, abbreviated as ART, since parametric ANOVA was inappropriate. Analyses were run in R 4.5.2 and RStudio 2025.09.2, packages current as of November 2025. The main effects and two-way interaction effects are reported in Appendix A.

The ART found a significant main effect of *Task* ($F(7, 154) = 73.79$, $p<0.001$), of *Phone side* ($F(5, 10032) = 786.64$, $p<0.001$), and of *Finger* on whether this was used ($F(11, 10032) = 305.40$, $p<0.001$).

The ART found a significant interaction effect of *Task* × *Phone side* ($F(35, 10032) = 42.74$, $p<0.001$), of *Task* × *Finger* on used ($F(77, 10032) = 35.16$, $p<0.001$) and of *Phone side* × *Finger* on used ($F(41, 10032) = 113.27$, $p<0.001$).

Finally, the ART found a significant three-way interaction effect of *Task* × *Phone side* × *Finger* on used ($F(287, 10032) = 13.11$, $p<0.001$; see Figure 4). There is no clearly distinguishable pattern for this three-way interaction effect. Therefore, we turned to machine learning approaches to see how well finger contact can predict tasks in the next section.

4.3.3 Predicting The Task from Hand Contact. We were interested in how well we could predict the task from the finger contacts using our dataset of 1032 labelled thermal images. For each participant and task, we computed the mean use proportion for every *Finger* × *Phone side* pairing, then pivoted to a wide feature vector per participant–task, filling missing pairings with zeros. We performed grouped v-fold cross validation stratified by participant ($v = \min(5, \#\text{participants})$) to avoid leakage across participants. On each training split, we fit an `XGBoost` multiclass classifier (R package version 3.1.1.1; `objective=multi:softmax`, `num_class` equal to the number of tasks, `max_depth=5`, `eta=0.1`, 500 boosting rounds). Labels were encoded as $0 \ldots K-1$ for training, and predictions were mapped back to task labels for evaluation on the held-out participants. Averaged over folds, accuracy was 0.525, macro F1 was 0.515. Results indicate hand contact patterns provide modest discriminative information (52.5% accuracy vs. 12.5% chance), but substantial confusion between visually similar tasks (photo/video) and functionally similar tasks (gaming/video) suggests contact alone is insufficient for reliable task classification. Figure 5 shows the confusion matrix.

4.4 Contact Maps

Based on the labelled masks, we plotted the contact patterns of finger and palm placement on each side of the smartphone for each interaction task and participant. Figure 6 shows exemplary contact maps combining all sides of the smartphone. Left-hand contacts are depicted in pink, right-hand contacts in blue. Individual fingers are distinguished by increasing saturation within each colour range, with the palm represented by the darkest tone. All contact maps of 1032 phone sides and participants' combined contact maps are included in the supplementary material.

Contact maps containing only blue or pink mark one-handed grasps (e.g., Scrolling). If both colours are present, the smartphone was held with both hands (e.g., Photo or Gaming). The shape of the contact region indicates which part of the finger made contact and the angle at which the finger met the surface. Smaller, round spots on the back surface denote contact with the fingertip, with a steeper angle (e.g., the dot on the right edge in Scrolling). Small but elongated points on the back indicate contact with the finger pad, suggesting a flatter angle (e.g., bottom two drops in Typing). This difference is particularly evident in the contact areas at the centre of the device's back in Video (drop-shaped) and Gaming (more elongated and larger size). Large elongated regions show contact along the finger length (e.g., Typing), while indentations in their contours reveal individual phalanges (e.g., Typing, Map).

The placement of contact points also provides insights into how the smartphone was held. A rectangular region in the bottom corner of the back side that reaches onto the adjacent side edge (e.g., in Scrolling and Calling) typically indicates palm contact when the device is supported one-handed. In the Gaming task, the elongated contact regions on the back, which extend from the outer edge towards the centre, and the contact regions on the short edges, suggest a two-handed grasp where the short edges sit inside the palms. Smaller dots on the back surface cut off by the edge, but continued on the side edge, show how these fingers wrapped around that smartphone edge.

Patterns in Contact Maps. To assess patterns in participants' hand-placements across interaction tasks, we computed aggregated contact maps (see Figure 7). Across tasks with portrait device orientation, the uppermost portion of the smartphone's back remained largely free of contact (Scrolling, Typing, Calling, Map, Photo, and Selfie), while palm contacts concentrated on the lower half along one or both side edges. Variations in patterns become evident through the location of high-frequency regions. Map showed higher contact frequency closer to the top than Typing, which was more confined to the lower half. Calling exhibited strong accumulations near the lower parts of both edges. The centre of the back was generally sparse, apart from a narrow band just above the vertical midpoint where the index finger was often placed. Volume showed a similar edge-focused pattern, consistent with high palm contact.

In landscape tasks (Gaming, Video), contact covered more of the back overall yet remained lighter near the upper edge. While both interactions elicited a two-handed grasp, the contact patterns differ regarding the touch points in the centre of the back surface. Video commonly featured a distinct central fingertip support point, whereas Gaming showed two prominent, elongated regions indicative of full-length finger contact.

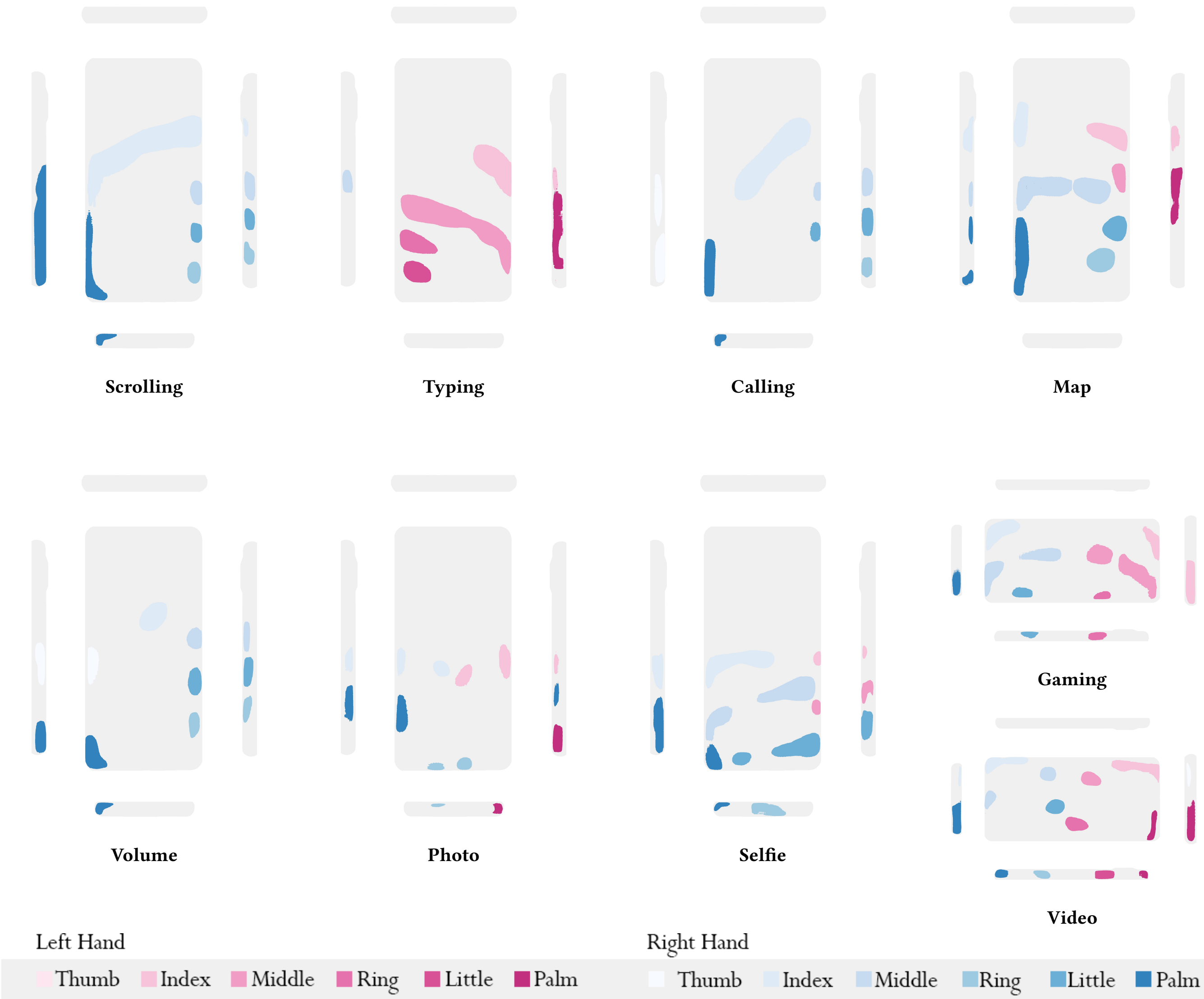


Figure 6: Representative participants' contact maps for each interaction task. Left-hand contacts are shown in pink and right-hand contacts in blue. Individual fingers are distinguished by increasing saturation within each colour range, and the palm uses the darkest tone. Each individual subfigure shows the back of the smartphone as well as the left, top, right, and bottom edge of the smartphone.

5 Discussion

Our user study examined how users' hands engage with smartphones beyond the touchscreen across nine mobile interaction tasks, focusing on (1) grasp characteristics and (2) the hand-smartphone contact patterns. We discuss how our findings deepen our understanding of mobile interactions beyond the touchscreen, and their implications for future smartphone design, its physical shape, and opportunities for novel haptic interface designs. We also reflect on using thermal imaging to capture hand contact with a smartphone and discuss implications for future research.

On-Screen Interactions Shape Off-Screen Finger Support. Our findings show distinct behaviours in participants' grasps across different mobile interactions, illustrating how fingers and palms engage with the smartphone beyond the touchscreen (RQ1). The quantitative grasp results highlight interaction tasks that include both hands: Typing, Gaming, Video, and Photo. In the case of Typing, both thumbs often interact with the keyboard at the bottom of the screen, naturally cradling the device between both hands. Gaming, Video, and Photo were all predominantly performed in landscape mode, which includes both hands for a secure enough grip. In contrast, interactions performed in portrait mode were more likely to elicit one-handed device support, which was often the case for

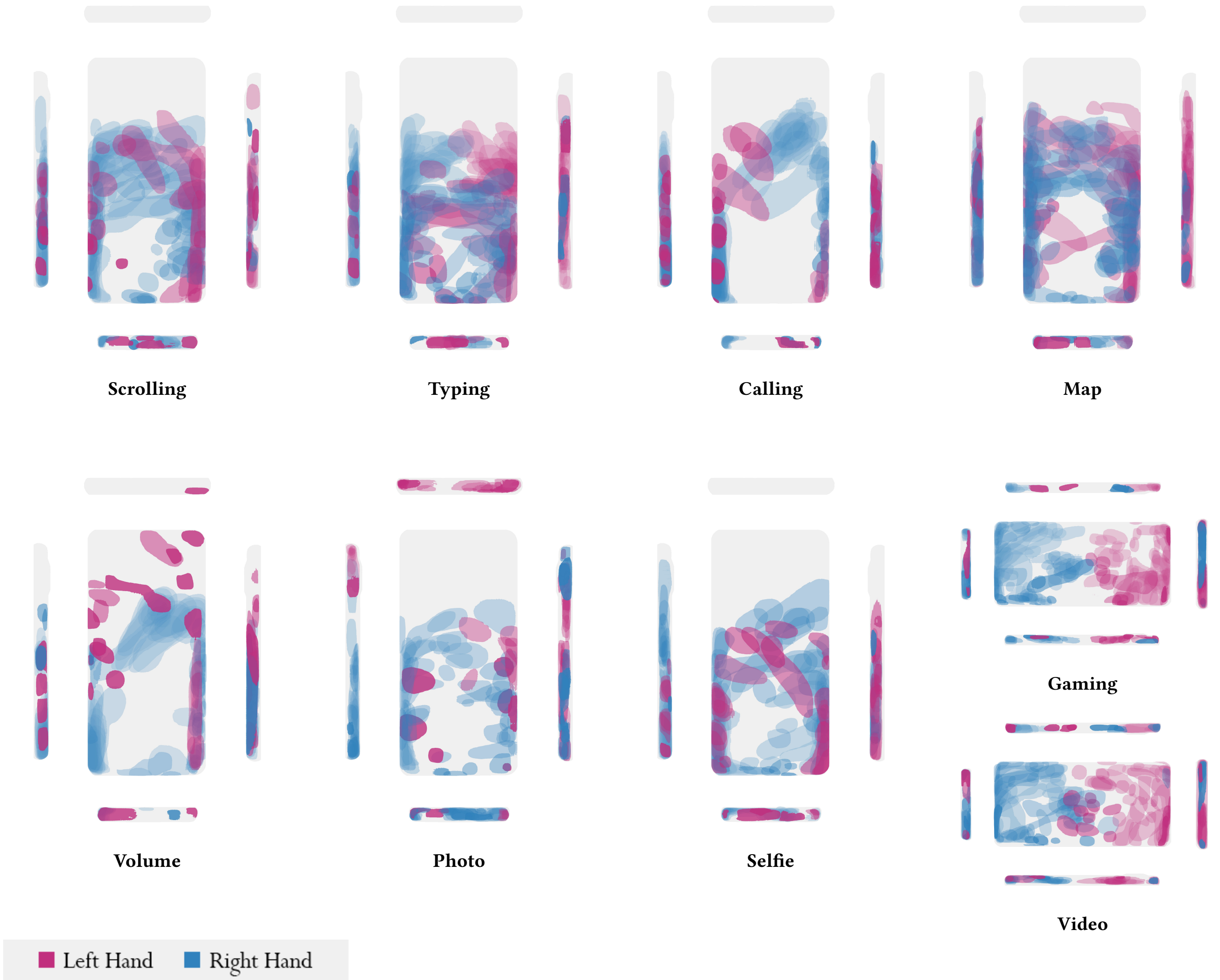


Figure 7: Accumulated contact pattern for all interaction tasks. Image for landscape use for the photo interaction is included in the supplementary material. Left-hand contacts are shown in pink and right-hand contacts in blue. Each individual subfigure shows the back of the smartphone as well as the left, top, right, and bottom edge of the smartphone.

Scrolling, Calling, Selfie, and Map. Touch input was then either performed by the same support hand holding the device or by the second, unencumbered hand. For Map, however, the distinction between one-handed and two-handed support was less clear. Here, half of the participants who supported the device during map exploration with one hand used their non-dominant hand, which was more frequent compared to other interactions. Since one-handed multitouch gestures for exploring a mobile map are more complex and involve multiple fingers, participants might have prioritised their dominant hand for this more demanding on-screen task.

We found distinct finger roles and postures when holding the smartphone, providing a deeper distinction in smartphone grasps compared to high-level grasp categorisations in prior research [39]. Most roles stabilised the device between different surfaces, e.g., supporting the back via flat, curved, or arched fingers to maintain the screen-facing orientation, supporting the bottom edge via the palm or little finger to prevent downward slip, or supporting the device's side by clamping the device between palm and fingers of the same hand in one-handed use to maintain an upright orientation. Grasping behaviour often involved fingers wrapping around multiple smartphone surfaces, such as both index fingers wrapping around the side edges onto the back in a two-handed grasp. While our work highlights the complexity and variety in finger configurations across different interaction tasks, future research needs to examine how other factors, such as interface layout, hand size, device dimensions, or wrist support, further influence *why* fingers are employed the way they are to contribute off-screen to a successful mobile interaction on-screen.

On-Screen Interactions Shape Off-Screen Contact. While grasp characteristics demonstrate *how* fingers support the smartphone, contact patterns illustrate *where* fingers and palms contact the device beyond the touchscreen (RQ2). Our findings highlight distinct spatial-frequency patterns (see Figure 7) across mobile interactions and device orientations. Individual distinctions were observed in placement, local frequency, and extent of the contacted surface.

Portrait usage commonly exhibited contact accumulations along the side edges, adjacent regions of the back, and the upper centre of the back, with no contact on the top edge and the top area of the back. Interactions with more widespread coverage suggest a higher number of fingers supporting the device off-screen to complete the interaction task on-screen. For example, Typing was predominantly performed in a two-handed support grasp, leaving both thumbs free for touch input, with the remaining fingers producing contact patterns spreading across the entire lower two-thirds of the back. In contrast, tasks eliciting more one-handed support grasps, e.g., Scrolling or Selfie, show more no-contact areas, suggesting that these mobile interactions with their specific on-screen input required overall less physical engagement for successful completion. Widespread contact also suggests greater variance in participants' finger placements, which could apply in the Volume task. Here, higher spatial variance in contact points suggests that participants used their own grasp strategies to push the side button, indicating that the smartphone's form factor does not afford a clear, prominent way to do so. In contrast, Calling produced small and distinctly located contact regions with high contact frequency, suggesting that participants applied similar grasps for this task.

Contact patterns of interactions performed in landscape mode, e.g., Gaming and Video, also exhibit a widespread contact surface produced by mostly two-handed grasps. A distinct difference between these two interactions can be observed in the contact patterns of the left and right hands in the centre of the smartphone's back. While touch contacts caused by both hands can be separated in the middle for Gaming, contact points of both hands in Video overlap. As Gaming required more touch input on the front screen, both hands might have been positioned in a way to provide both thumbs enough range of motion for the touch input on the front. In contrast, watching the video required the device to be held, without active touch input. Here, hands might have been pulled more back to keep the touchscreen free, causing fingers to overlap in the back.

Hands Establish Little Contact With the Smartphone During the Interaction. Hands actually make little contact with the handheld device (see blank areas in Figure 6). The flat, rectangular smartphone is, thereby, mostly stabilised through a few discrete contact points. This may threaten grasp stability, eliciting the observed techniques, such as using the little finger to support the bottom edge or clamping both edges with one hand. Such techniques may place additional strain on the hand, potentially causing stress pain to the thumb and fingers [6]. Additionally, a global market size of 2.50 billion in 2024 for phone grips like pop-sockets, ring grips, or strap grips [2] suggests that users still need additional grasp assistance. Moreover, our analysis of two-handed grasps revealed fingers that did not touch the device at all, either because they were stacked or resting in mid-air, contrasting full-finger contact grasps of other everyday objects, such as bottles or flashlights [9]. We argue that the smartphone's shape should be reevaluated to better accommodate the human grasp. Alternative designs could afford a more ergonomic wrap through an expanded body, similar to other handheld devices such as game controllers, television remotes, or computer mice. Prior work capturing hand-device contact on a computer mouse highlighted the hand's near-full contact and ergonomic wrap [21]. Another design feature might also offer an expanded, gently contoured back for resting and bracing the fingers. A more secure grasp might offload support complexity from individual fingers, replace external accessories and even reduce issues such as thumb reachability [26].

Advancing Mobile Input and Output Through Spatial Contact Patterns. Understanding where users' hands commonly contact the device can also inform interactions beyond the touchscreen. Previous back-of-device (BoD) techniques [7, 60, 72] increase input bandwidth by shifting interaction to the device's back, e.g., to mitigate the Fat Finger or the Occlusion Problem. Our results further support the back as a viable input surface, with 37 − 54% of the touch contacts occurring there (see Table 3). However, while prior work established baselines only for a one-handed grasp regarding finger placements [38] and finger reachability [35], our findings show that finger postures and placements vary across users, interaction tasks, and device orientations, highlighting additional factors and surfaces to consider. These nuances can inform surface gestures tailored to specific tasks, the involved fingers and their placement to extend input to frequently contacted edges. For instance, the right and left edges experienced around 19 − 30% of hand contacts (see Table 3), e.g., caused by R1, R3, R4 and R5 for Calling or L2, LPa, R2 and RPa for Typing (see Figure 4).

Contact patterns can equally inform the design of future haptic interfaces in smartphones. Highly frequented areas highlight meaningful locations for haptic actuators, enabling local and directional sensations that go beyond the current device-wide vibration feedback. Such spatial haptics could, e.g., augment on-screen motion or support more expressive experiences in mobile games and videos [61]. Prior work has explored actuated pins on the phone's long edge [28]. Building on our findings, such haptic actuators could be placed on the more frequently used short edges to reinforce left-right movements or provide haptic cues to augment content beyond the touchscreen. As smartphones are increasingly used in immersive environments (e.g. [29, 64]), spatial haptics could further enhance spatial interactions.

Keeping Out of Contact Zones. Highly frequented contact regions also indicate where hardware components that are disrupted by direct skin contact should *not* be placed. The common no-contact zones in portrait mode, e.g., the top edge or upper back during Scrolling, Typing, or taking a Photo, support the current placement of components such as the camera or flashlight. In contrast, the bottom edge is heavily contacted across all mobile interactions, yet it typically hosts the speaker, microphone or charging port. This placement may disrupt natural grasps, for instance, when users shift their supporting finger to avoid covering the speaker while watching a video or playing a game in landscape mode. Similarly, a plugged-in cable occupies the centre of the edge. Our contact patterns offer insights for a user-centred reevaluation of component placements. For example, cable-based charging could be moved to the top edge where no contact occurs, using a right-angle connector so the cable runs down the back of the device.

Thermal Imaging as an Accurate and Feasible Method for Post-Hoc Hand-Device Contact Detection. Thermal imaging has previously been used to capture grasp and contact patterns on objects of varied geometry [9]. We extend this technique to smartphones and reflect on its methodological feasibility, including overcoming visual occlusion, establishing ground truth, and ensuring ecological validity. We discuss its current limitations and implications for future research.

A core challenge in studying smartphone grasps and contact patterns is visual occlusion. External cameras are insufficient due to bending and overlapping fingers, and the smartphone itself blocking the view. Our study demonstrated the feasibility of recording hand-smartphone contact *after* the interaction by capturing the residual heat traces left on the phone's surface. The captured data contained accurate and detailed handprints with clearly distinguishable fingers and contour indentations. In addition, the heat residues revealed the exact shape and size of contacts and contact regions that extend over multiple sides. Heat signatures of the internal active components did not confound detection, as they appeared weak and diffuse. Thermal imaging, therefore, provides an accurate benchmark, as it registers only heat transfer from actual direct skin-to-surface contact. In contrast, pressure-sensing [32] or capacitive sensing [21, 52] offer lower spatial resolution and can register unwanted hover or near-touch. Techniques relying on the projection of 3D data, such as MoCap [55] or OptiTrack [35, 58], only infer contact from intersecting 3D models, which cannot capture the exact size and shape of direct skin contacts and are prone to clipping errors, negatively impacting accuracy. Another advantage of thermal imaging is that it does not require modifications to the device's surface. Users feel the smartphone's actual surface rather than additional capacitive or pressure-sensing layers, such as force-sensitive sensors or capacitive tape. Unlike MoCap setups, it requires no markers or gloves that might alter finger movement and natural grasping behaviour.

Nonetheless, as no real-time contact detection is possible, it is best suited for empirical studies of contact patterns and the construction of datasets to inform mobile interaction design. While batch pre-processing of thermal images supported automatic mask segmentation and labelling, the final refinement still required substantial manual work. However, given the consistent spatial constraints of left- and right-hand layouts, this effort could be reduced by training a dedicated detection model. As thermal imaging captures only fingers in direct contact with the smartphone, fingers not touching the device, such as those stacked or resting in mid-air, are omitted. To capture these cases, thermal contact detection should be combined with photographic imagery of the hands to include non-contact fingers. Hand pose detection could then be assisted by automated 3D reconstruction models [22]. Moreover, it is important to ensure micro-movements do not affect observed contact areas. For validation, one author reviewed the video recordings and counted pose changes, i.e., changes of the hand pose or configuration, and regrasps, i.e., behaviours where the participant would briefly change contact of one or more fingers with the phone. We confirmed that the majority of trials (94.20%) did not exhibit micro-movements, whereas in the 12 trials (out of 207) where either a pose change or a regrasp occurred, the behaviour was of short duration (< 1 second). Therefore, micro-movements were unlikely to influence the overall contact, which lasted for at least 30 seconds.

Finally, with the growing availability of low-cost thermal cameras, thermal imaging is an accessible and affordable alternative for HCI researchers. As smartphones and other handheld devices continue to evolve, thermal imaging offers a reliable tool for evaluating future device dimensions and form factors based on direct touch during the interaction. For instance, with a new generation of flip phones [63], a new set of affordances is introduced [56] that requires more manual engagement with the device. In such cases, grasps and contact patterns are heavily impacted by folded and unfolded states. Thermal imaging enables the assessment of direct contacts when navigating this novel setup of multiple touchscreens.

5.1 Future Work

We labelled contact regions as fingers or palms. Because their contours show distinct features (e.g., indentations in finger outlines), future work could further segment these regions to estimate finger–surface angles and infer hand posture. Such higher-resolution contact data could improve task and grasp prediction, complement prior work on handedness detection [42], and support better real-time UI adaptation to enhance touch input [19, 84]. For example, detecting device tilts and rotations could drive vertical or horizontal UI shifts to improve reachability and reduce micro-movements [19].

Future work on thermal imaging could examine whether contact pressure can be inferred from contact-area size or temperature variations within a region, as higher temperatures may indicate greater pressure. The limited thermal decay window also constrains how long traces remain visible. In our dataset, only a rare case, typically when the little finger rested on the phone's bottom edge, showed weak traces, which we verified via photographs. Future studies could mitigate this by using a case that provides a continuous perimeter surface beyond the touchscreen.

Further research should examine how device specifications and external smartphone accessories (e.g., grip straps) affect finger/palm roles and contact areas. Similarly, studies on human factors should investigate hand sizes, fingernail length [16].

As foldable smartphones enter the mass market, future work should examine how their changing form factor affects finger placement on folded vs. unfolded surfaces, extending prior work on flip-phone folding interactions [74]. Likewise, growing use of smartphones and tablets as interaction devices in immersive environments [1, 29, 41, 43, 45, 46, 64, 66, 69, 80, 82, 83] raises new demands on form factor, input, and multisensory feedback.

5.2 Limitations

Although the sample (N = 23) is reasonably gender-balanced, age, disability, and hand dominance may influence the results. Younger participants may move faster or more precisely, while older or more motor-impaired participants may show slightly reduced dexterity and adopt alternative grips. Although the sample was modest and right-hand-skewed, it provided enough variation to reveal clear patterns. Broader diversity in digital literacy and mobile experience could further enrich the analysis. Overall, the sample supports robust, broadly generalisable insights into phone handling.

We used a single fixed-size smartphone to isolate activity-driven patterns. While the dimensions of the Pixel 7 render the device as representative of contemporary smartphones, prior work [35] indicates that variations in device size can influence thumb reach and grip preferences. However, the use of this typical form factor provides a stable reference point for interpreting the interaction behaviours observed for most of the current smartphones. To control task behaviour, we selected specific apps. Because app layouts influence touch input (e.g., location or frequency), they may also affect grasp and supporting behaviour. As our chosen apps use common UIs for their respective tasks, the dataset is sufficiently robust for the nine interaction tasks studied. However, other tasks and apps may elicit additional grasp variations in future work.

Our exploratory attempt to predict the task from hand contact patterns clarifies the limits of what can be inferred from grip alone, achieving modest accuracy (52.5%) across 8 tasks. The limited discriminative power suggests that while contact patterns reveal *where* hands engage with devices, they provide too little information to reliably infer *what* users are doing. Future work combining thermal contact detection with real-time sensors (accelerometer, gyroscope, touchscreen input) could enable more robust grasp-aware interfaces. While the predictive performance was modest, this result is informative: the substantial overlap of contact patterns across tasks indicates that sensing contact on the back and sides of the device, in isolation, is a weak cue for inferring the current activity. This suggests designers should treat hand contact as one signal among several, not a standalone input for task recognition.

Participants were not instructed to adopt a fixed seating position but could choose a natural, comfortable posture, enhancing ecological validity by reflecting everyday phone use. Prior work shows that body posture shapes hand–device interaction, engaging different muscle groups and joint postures, and thus altering grip stability and device movement [18, 24]. Our approach, therefore, captures grasp and contact behaviour in realistic settings while also introducing variability in muscle activation, grip type, and interaction patterns. We regard this variability as a feature reflecting real-world heterogeneity, though future studies could experimentally control posture to more precisely isolate its effects on grasp behaviour.

6 Conclusion

In this paper, we studied grasps and hand-device contact patterns on the smartphone's back and four side edges for nine interaction tasks to build a better understanding of mobile interactions beyond the touchscreen. We found that the fingers and palms adopt different support roles while adapting the hand posture to the touch input. Contact regions of where the hands physically touched the device were captured through thermal heat traces on the smartphone's back and four side edges. The labelled contact maps show distinct patterns across interaction tasks, differing in the spatial distribution of high/low contact frequency and finger-side engagement. Through the combination of characterising smartphone grasps and contact patterns across common mobile interactions, our findings extend the current understanding of how users' hands physically engage with a smartphone beyond the touchscreen, providing new insights for future designs of multimodal mobile interactions.

Open Science

The dataset is enclosed in the supplementary material and available on GitHub: https://github.com/CarolinStellmacher/Datatset-of-Grasp-and-Contact-Patterns-Across-Mobile-Interactions.git.

Acknowledgments

This research was partially supported by the Minds, Media, Machines (MMM) High Profile Research Area at the University of Bremen (54030724) and an additional MMM seed grant (007), and the project "hyBit: Hydrogen for Bremen's Industrial Transformation" by the Federal Ministry of Research, Technology and Space (BMFTR, 03SF0687A). Funding was also received by the German Research Foundation (DFG) under project number 521601028, under Germany's Excellence Strategy (EXC 2077, University of Bremen), and under "EASE - Everyday Activity Science and Engineering" as part of Collaborative Research Center (Sonderforschungsbereich) 1320 with the project number 329551904 at University of Bremen. In this paper, Overleaf's built-in spell checker, Grammarly, DeepL, and the current version of ChatGPT (GPT-5.0) were used. These tools helped correct spelling mistakes and provide suggestions to improve the paper's writing. If not noted otherwise in a specific section, these tools were not used in other forms.

References

[1] 2021. Phonetroller: Visual Representations of Fingers for Precise Touch Input with Mobile Phones in VR. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 129, 13 pages. doi:10.1145/3411764.3445583

[2] Accio.com. 2025. Trend of Phone Pop Socket 2025: Must-Know Insights. https://www.accio.com/t-v2/business/trend-of-phone-pop-socket. Accessed: 2025-11-27.

[3] Sung Hee Ahn, Sanghyun Kwon, Youngjin Na, and Myung Hwan Yun. 2021. Grasp Behavior Analysis Using Muscle and Postural Hand Synergies for Smartphones. *International Journal of Precision Engineering and Manufacturing* 22, 4 (2021), 697–707.

[4] Yaron Ariel, Vered Elishar-Malka, Ruth Avidar, and Eilat-Chen Levy. 2017. Smartphone usage among young Israeli adults: a combined quantitative and qualitative approach. *Israel Affairs* 23, 5 (2017), 970–986.

[5] Manfredo Atzori, Arjan Gijsberts, Claudio Castellini, Barbara Caputo, Anne-Gabrielle Mittaz Hager, Simone Elsig, Giorgio Giatsidis, Franco Bassetto, and Henning Müller. 2014. Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific Data* 1, 1 (Dec. 2014). doi:10.1038/sdata.2014.53

[6] Faeze Dehghan Banadaki, Benyamin Rahimian, Fatemeh Moraveji, and Sakineh Varmazyar. 2024. The impact of smartphone use duration and posture on the prevalence of hand pain among college students. *BMC Musculoskeletal Disorders* 25, 1 (2024), 574.

[7] Patrick Baudisch and Gerry Chu. 2009. Back-of-device interaction allows creating very small touch devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Boston, MA, USA) *(CHI '09)*. Association for Computing Machinery, New York, NY, USA, 1923–1932. doi:10.1145/1518701.1518995

[8] Ann Blandford, Dominic Furniss, and Stephann Makri. 2016. Qualitative HCI research: Going behind the scenes. *Synthesis Lectures on Human-Centered Informatics* 9, 1 (April 2016), 115 pages. doi:10.2200/S00706ED1V01Y201602HCI034

[9] Samarth Brahmbhatt, Cusuh Ham, Charles C. Kemp, and James Hays. 2019. ContactDB: Analyzing and Predicting Grasp Contact via Thermal Imaging. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.

[10] Peter André Busch, Geir Inge Hausvik, Odd Karsten Ropstad, and Daniel Pettersen. 2021. Smartphone usage among older adults. *Computers in Human Behavior* 121 (2021), 106783. doi:10.1016/j.chb.2021.106783

[11] Daniel Buschek and Florian Alt. 2015. TouchML: A Machine Learning Toolkit for Modelling Spatial Touch Targeting Behaviour. In *Proceedings of the 20th International Conference on Intelligent User Interfaces* (Atlanta, Georgia, USA) *(IUI '15)*. Association for Computing Machinery, New York, NY, USA, 110–114. doi:10.1145/2678025.2701381

[12] Khansa Chemnad, Sameha Alshakhsi, Mohamed Basel Almourad, Majid Altuwairiqi, Keith Phalp, and Raian Ali. 2022. Smartphone Usage before and during COVID-19: A Comparative Study Based on Objective Recording of Usage Data. *Informatics* 9, 4 (2022). doi:10.3390/informatics9040098

[13] Liang CHEN, Dongyi Chen, and Xiao CHEN. 2018. BackAssist: Augmenting Mobile Touch Manipulation with Back-of-Device Assistance. *IEICE Transactions on Information and Systems* E101.D (06 2018), 1682–1685. doi:10.1587/transinf.2017EDL8209

[14] Younggeun Choi, Xiaopeng Yang, Jangwoon Park, Wonsup Lee, and Heecheon You. 2020. Effects of smartphone size and hand size on grip posture in one-handed hard key operations. *Applied Sciences* 10, 23 (2020), 8374.

[15] Christian Corsten, Bjoern Daehlmann, Simon Voelker, and Jan Borchers. 2017. BackXPress: Using Back-of-Device Finger Pressure to Augment Touchscreen Input on Smartphones. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 4654–4666. doi:10.1145/3025453.3025565

[16] Céline Coutrix and Camélia Prost. 2024. Impact of Fingernails Length on Mobile Tactile Interaction. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 553, 21 pages. doi:10.1145/3613904.3642037

[17] Rachel Eardley, Steve Gill, Anne Roudaut, Stephen Thompson, and Joanna Hare. 2016. Investigating how the hand interacts with different mobile phones. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (Florence, Italy) *(MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 698–705. doi:10.1145/2957265.2961840

[18] Rachel Eardley, Anne Roudaut, Steve Gill, and Stephen J. Thompson. 2017. Understanding Grip Shifts: How Form Factors Impact Hand Movements on Mobile Phones. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 4680–4691. doi:10.1145/3025453.3025835

[19] Rachel Eardley, Anne Roudaut, Steve Gill, and Stephen J. Thompson. 2018. Designing for Multiple Hand Grips and Body Postures within the UX of a moving Smartphone. In *Proceedings of the 2018 Designing Interactive Systems Conference* (Hong Kong, China) *(DIS '18)*. Association for Computing Machinery, New York, NY, USA, 611–621. doi:10.1145/3196709.3196711

[20] Rachel Eardley, Anne Roudaut, Steve Gill, and Stephen J. Thompson. 2018. Investigating How Smartphone Movement is Affected by Body Posture. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–8. doi:10.1145/3173574.3173776

[21] Martina Emmert, Andreas Schmid, Paula Wiesner, Michael Pickl, and Niels Henze. 2025. Teaching an Old Mouse New Tricks: User-Centered Development of a Gesture Set for Touch-Enabled Computer Mice. In *Proceedings of the 24th International Conference on Mobile and Ubiquitous Multimedia (MUM '25)*. Association for Computing Machinery, New York, NY, USA, 104–117. doi:10.1145/3771882.3771916

[22] Zicong Fan, Maria Parelli, Maria Eleni Kadoglou, Xu Chen, Muhammed Kocabas, Michael J. Black, and Otmar Hilliges. 2024. HOLD: Category-agnostic 3D Reconstruction of Interacting Hands and Objects from Video. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 494–504.

[23] Mayank Goel, Jacob Wobbrock, and Shwetak Patel. 2012. GripSense: using built-in sensors to detect hand posture and pressure on commodity mobile phones. In *Proceedings of the 25th Annual ACM Symposium on User Interface Software and Technology* (Cambridge, Massachusetts, USA) *(UIST '12)*. Association for Computing Machinery, New York, NY, USA, 545–554. doi:10.1145/2380116.2380184

[24] J.E. Gold, J.B. Driban, N. Thomas, T. Chakravarty, V. Channell, and E. Komaroff. 2012. Postures, typing strategies, and gender differences in mobile device usage: An observational study. *Applied Ergonomics* 43, 2 (2012), 408–412. doi:10.1016/j.apergo.2011.06.015 Special Section on Product Comfort.

[25] Jussi Hakala and Jukka Häkkinen. 2022. A Method for Measuring Contact Points in Human–Object Interaction Utilizing Infrared Cameras. *Frontiers in Robotics and AI* 8 (Feb. 2022). doi:10.3389/frobt.2021.800131

[26] Christian Holz and Patrick Baudisch. 2011. Understanding touch. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. Association for Computing Machinery, New York, NY, USA, 2501–2510. doi:10.1145/1978942.1979308

[27] Kaori Ikematsu, Haruna Oshima, Rachel Eardley, and Itiro Siio. 2020. Investigating How Smartphone Movement is Affected by Lying Down Body Posture. *Proc. ACM Hum.-Comput. Interact.* 4, ISS, Article 192 (Nov. 2020), 17 pages. doi:10.1145/3427320

[28] Sungjune Jang, Lawrence H. Kim, Kesler Tanner, Hiroshi Ishii, and Sean Follmer. 2016. Haptic Edge Display for Mobile Tactile Interaction. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 3706–3716. doi:10.1145/2858036.2858264

[29] Mohamed Kari and Christian Holz. 2023. HandyCast: Phone-based Bimanual Input for Virtual Reality in Mobile and Space-Constrained Settings via Pose-and-Touch Transfer. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 528, 15 pages. doi:10.1145/3544548.3580677

[30] Kee-Eung Kim, Wook Chang, Sung-Jung Cho, Junghyun Shim, Hyunjeong Lee, Joonah Park, Youngbeom Lee, Sangryoung Kim, et al. 2006. Hand grip pattern recognition for mobile user interfaces. In *Proceedings of the National Conference on Artificial Intelligence*, Vol. 21. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 1789.

[31] Dohoon Kwon, Xin Cui, Yejin Lee, Younggeun Choi, Aditya Subramani Murugan, Eunsik Kim, and Heecheon You. 2025. Machine Learning-Based Smartphone Grip Posture Image Recognition and Classification. *Applied Sciences* 15, 9 (April 2025), 5020. doi:10.3390/app15095020

[32] Cederick Landry, Daniel Loewen, Harish Rao, Brendan L. Pinto, Robert Bahensky, and Naveen Chandrashekar. 2021. Isolating In-Situ Grip and Push Force Distribution from Hand-Handle Contact Pressure with an Industrial Electric Nutrunner. *Sensors* 21, 23 (Dec. 2021), 8120. doi:10.3390/s21238120

[33] Joachim Normann Larsen, Tórur Højgaard Jacobsen, Sebastian Boring, Joanna Bergström, and Henning Pohl. 2019. The influence of hand size on touch accuracy. In *Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services*. 1–11.

[34] Huy Viet Le, Thomas Kosch, Patrick Bader, Sven Mayer, and Niels Henze. 2018. PalmTouch: Using the Palm as an Additional Input Modality on Commodity Smartphones. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3173574.3173934

[35] Huy Viet Le, Sven Mayer, Patrick Bader, and Niels Henze. 2018. Fingers' Range and Comfortable Area for One-Handed Smartphone Interaction Beyond the Touchscreen. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3173574.3173605

[36] Huy Viet Le, Sven Mayer, and Niels Henze. 2018. InfiniTouch: Finger-aware interaction on fully touch sensitive smartphones. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology*. 779–792.

[37] Huy Viet Le, Sven Mayer, Benedict Steuerlein, and Niels Henze. 2019. Investigating unintended inputs for one-handed touch interaction beyond the touchscreen. In *Proceedings of the 21st International Conference on Human-Computer Interaction with Mobile Devices and Services*. 1–14.

[38] Huy Viet Le, Sven Mayer, Katrin Wolf, and Niels Henze. 2016. Finger Placement and Hand Grasp during Smartphone Interaction. In *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI EA '16)*. Association for Computing Machinery, New York, NY, USA, 2576–2584. doi:10.1145/2851581.2892462

[39] Songil Lee, Gyouhyung Kyung, Jungyong Lee, Seung Ki Moon, and Kyoung Jong Park. 2016. Grasp and index finger reach zone during one-handed smartphone rear interaction: effects of task type, phone width and hand length. *Ergonomics* 59, 11 (2016), 1462–1472.

[40] Florian Lehmann and Michael Kipp. 2018. How to Hold Your Phone When Tapping: A Comparative Study of Performance, Precision, and Errors. In *Proceedings of the 2018 ACM International Conference on Interactive Surfaces and Spaces* (Tokyo, Japan) *(ISS '18)*. Association for Computing Machinery, New York, NY, USA, 115–127. doi:10.1145/3279778.3279791

[41] Hai-Ning Liang, Yuwei Shi, Feiyu Lu, Jizhou Yang, and Konstantinos Papangelis. 2016. VRMController: an input device for navigation activities in virtual reality environments. 455–460. doi:10.1145/3013971.3014005

[42] Markus Löchtefeld, Phillip Schardt, Antonio Krüger, and Sebastian Boring. 2015. Detecting users handedness for ergonomic adaptation of mobile user interfaces. In *Proceedings of the 14th International Conference on Mobile and Ubiquitous Multimedia* (Linz, Austria) *(MUM '15)*. Association for Computing Machinery, New York, NY, USA, 245–249. doi:10.1145/2836041.2836066

[43] Akhmajon Makhsadov, Donald Degraen, André Zenner, Felix Kosmalla, Kamila Mushkina, and Antonio Krüger. 2022. VRySmart: a Framework for Embedding Smart Devices in Virtual Reality. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI EA '22)*. Association for Computing Machinery, New York, NY, USA, Article 358, 8 pages. doi:10.1145/3491101.3519717

[44] Juha Matero and Ashley Colley. 2012. Identifying unintentional touches on handheld touch screen devices. In *Proceedings of the Designing Interactive Systems Conference* (Newcastle Upon Tyne, United Kingdom) *(DIS '12)*. Association for Computing Machinery, New York, NY, USA, 506–509. doi:10.1145/2317956.2318031

[45] Fabrice Matulic, Taiga Kashima, Deniz Beker, Daichi Suzuo, Hiroshi Fujiwara, and Daniel Vogel. 2023. Above-Screen Fingertip Tracking with a Phone in Virtual Reality. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, Article 18, 7 pages. doi:10.1145/3544549.3585728

[46] Fabrice Matulic, Taiga Kashima, Deniz Beker, Daichi Suzuo, Hiroshi Fujiwara, and Daniel Vogel. 2024. Above-Screen Fingertip Tracking and Hand Representation for Precise Touch Input with a Phone in Virtual Reality. In *Proceedings of the 50th Graphics Interface Conference* (Halifax, NS, Canada) *(GI '24)*. Association for Computing Machinery, New York, NY, USA, Article 3, 15 pages. doi:10.1145/3670947.3670961

[47] Sven Mayer, Huy Viet Le, Alessandro Nesti, Niels Henze, Heinrich H. Bülthoff, and Lewis L. Chuang. 2018. The Effect of Road Bumps on Touch Interaction in Cars. In *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (Toronto, ON, Canada) *(AutomotiveUI '18)*. Association for Computing Machinery, New York, NY, USA, 85–93. doi:10.1145/3239060.3239071

[48] Alexander Ng, Stephen A. Brewster, and John H. Williamson. 2014. Investigating the effects of encumbrance on one- and two- handed interactions with mobile devices. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 1981–1990. doi:10.1145/2556288.2557312

[49] Alexander Ng, John Williamson, and Stephen Brewster. 2015. The Effects of Encumbrance and Mobility on Touch-Based Gesture Interactions for Mobile Phones. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Copenhagen, Denmark) *(MobileHCI '15)*. Association for Computing Machinery, New York, NY, USA, 536–546. doi:10.1145/2785830.2785853

[50] Alexander Ng, John H Williamson, and Stephen A Brewster. 2014. Comparing evaluation methods for encumbrance and walking on interaction with touchscreen mobile devices. In *Proceedings of the 16th international conference on Human-computer interaction with mobile devices & services*. 23–32.

[51] Antti Oulasvirta and Joanna Bergstrom-Lehtovirta. 2011. Ease of juggling: studying the effects of manual multitasking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 3103–3112.

[52] Gianpaolo Palma, Narges Pourjafarian, Jürgen Steimle, and Paolo Cignoni. 2024. Capacitive Touch Sensing on General 3D Surfaces. *ACM Trans. Graph.* 43, 4, Article 103 (July 2024), 20 pages. doi:10.1145/3658185

[53] Yong S. Park and Sung H. Han. 2010. One-handed thumb interaction of mobile devices from the input accuracy perspective. *International Journal of Industrial Ergonomics* 40, 6 (2010), 746–756. doi:10.1016/j.ergon.2010.08.001

[54] Nikhila Ravi, Valentin Gabeur, Yuan-Ting Hu, Ronghang Hu, Chaitanya Ryali, Tengyu Ma, Haitham Khedr, Roman Rädle, Chloe Rolland, Laura Gustafson, Eric Mintun, Junting Pan, Kalyan Vasudev Alwala, Nicolas Carion, Chao-Yuan Wu, Ross Girshick, Piotr Dollár, and Christoph Feichtenhofer. 2024. SAM 2: Segment Anything in Images and Videos. *arXiv preprint arXiv:2408.00714* (2024). https://arxiv.org/abs/2408.00714

[55] Artur Saudabayev, Zhanibek Rysbek, Raykhan Khassenova, and Huseyin Atakan Varol. 2018. Human grasping database for activities of daily living with depth, color and kinematic data streams. *Scientific Data* 5, 1 (May 2018). doi:10.1038/sdata.2018.101

[56] Gian-Luca Savino, Jana Wahls, and Johannes Schöning. 2024. Mobile Map Applications for Foldable Devices. In *Proceedings of the 2024 International Conference on Advanced Visual Interfaces* (Arenzano, Genoa, Italy) *(AVI '24)*. Association for Computing Machinery, New York, NY, USA, Article 29, 5 pages. doi:10.1145/3656650.3656655

[57] Matthias Seuter, Max Pfeiffer, Gernot Bauer, Karen Zentgraf, and Christian Kray. 2017. Running with Technology: Evaluating the Impact of Interacting with Wearable Devices on Running Movement. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 101 (Sept. 2017), 17 pages. doi:10.1145/3130966

[58] Adwait Sharma, Michael A. Hedderich, Divyanshu Bhardwaj, Bruno Fruchard, Jess McIntosh, Aditya Shekhar Nittala, Dietrich Klakow, Daniel Ashbrook, and Jürgen Steimle. 2021. SoloFinger: Robust Microgestures while Grasping Everyday Objects. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. ACM, 1–15. doi:10.1145/3411764.3445197

[59] Adwait Sharma, Joan Sol Roo, and Jürgen Steimle. 2019. Grasping Microgestures: Eliciting Single-hand Microgestures for Handheld Objects. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3290605.3300632

[60] Shaikh Shawon Arefin Shimon, Sarah Morrison-Smith, Noah John, Ghazal Fahimi, and Jaime Ruiz. 2015. Exploring User-Defined Back-Of-Device Gestures for Mobile Devices. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services* (Copenhagen, Denmark) *(MobileHCI '15)*. Association for Computing Machinery, New York, NY, USA, 227–232. doi:10.1145/2785830.2785890

[61] Tanay Singhal and Oliver Schneider. 2021. Juicy Haptic Design: Vibrotactile Embellishments Can Improve Player Experience in Games. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 126, 11 pages. doi:10.1145/3411764.3445463

[62] Statista. 2023. Leading smartphone users activities worldwide in 2023. https://www.statista.com/statistics/1337895/top-smartphone-activities/ Accessed: 2025-06-03.

[63] Statista. 2025. Foldable unit shipments worldwide 2016–2025. https://www.statista.com/statistics/1422983/foldable-unit-shipments-worldwide/. Accessed: 2025-11-27.

[64] Carolin Stellmacher, Florian Mathis, Yannick Weiss, Meagan B. Loerakker, Nadine Wagener, and Johannes Schöning. 2024. Exploring Mobile Devices as Haptic Interfaces for Mixed Reality. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 422, 17 pages. doi:10.1145/3613904.3642176

[65] Subramanian Sundaram, Petr Kellnhofer, Yunzhu Li, Jun-Yan Zhu, Antonio Torralba, and Wojciech Matusik. 2019. Learning the signatures of the human grasp using a scalable tactile glove. *Nature* 569, 7758 (May 2019), 698–702. doi:10.1038/s41586-019-1234-z

[66] Hemant Bhaskar Surale, Aakar Gupta, Mark Hancock, and Daniel Vogel. 2019. TabletInVR: Exploring the Design Space for Using a Multi-Touch Tablet in Virtual Reality. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3290605.3300243

[67] Omid Taheri, Nima Ghorbani, Michael J. Black, and Dimitrios Tzionas. 2020. *GRAB: A Dataset of Whole-Body Human Grasping of Objects*. Springer International Publishing, 581–600. doi:10.1007/978-3-030-58548-8_34

[68] Tokuo Tsuji, Hidetoshi Seki, Daisuke Inada, Ken-ichi Morooka, Kensuke Harada, Kenji Tahara, Masatoshi Hikizu, and Hiroaki Seki. 2018. Grasp Synergy Analysis Based on Contact Area of Fingers Using Thermal Signatures. In *2018 57th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*. IEEE, 1386–1392. doi:10.23919/sice.2018.8492623

[69] Rishi Vanukuru, Amarnath Murugan, and Jayesh Pillai. 2020. Dual Phone AR: Exploring the use of Phones as Controllers for Mobile Augmented Reality. In *Proceedings of the 26th ACM Symposium on Virtual Reality Software and Technology* (Virtual Event, Canada) *(VRST '20)*. Association for Computing Machinery, New York, NY, USA, Article 52, 3 pages. doi:10.1145/3385956.3422113

[70] Robert Wakolbinger, Aidan D. Roche, Theresa Stockinger, Burkhard Gustorff, and Oskar C. Aszmann. 2014. Multiregion thermal sensitivity mapping of the hand. *Journal of Plastic, Reconstructive & Aesthetic Surgery* 67, 11 (2014), 1541–1547. doi:10.1016/j.bjps.2014.06.017

[71] Dan Wang, Zheng Xiang, and Daniel R Fesenmaier. 2016. Smartphone use in everyday life and travel. *Journal of travel research* 55, 1 (2016), 52–63.

[72] Daniel Wigdor, Clifton Forlines, Patrick Baudisch, John Barnwell, and Chia Shen. 2007. Lucid touch: a see-through mobile device. In *Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology* (Newport, Rhode Island, USA) *(UIST '07)*. Association for Computing Machinery, New York, NY, USA, 269–278. doi:10.1145/1294211.1294259

[73] Jacob O. Wobbrock, Leah Findlater, Darren Gergle, and James J. Higgins. 2011. The Aligned Rank Transform for Nonparametric Factorial Analyses Using Only Anova Procedures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Vancouver, BC, Canada) *(CHI '11)*. ACM, New York, NY, USA, 143–146. doi:10.1145/1978942.1978963

[74] Yen-Ting Yeh, Antony Albert Raj Irudayaraj, and Daniel Vogel. 2024. Single-handed Folding Interactions with a Modified Clamshell Flip Phone. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 406, 14 pages. doi:10.1145/3613904.3642554

[75] Yen-Ting Yeh, Fabrice Matulic, and Daniel Vogel. 2023. Phone Sleight of Hand: Finger-Based Dexterous Gestures for Physical Interaction with Mobile Phones. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 519, 19 pages. doi:10.1145/3544548.3581121

[76] Yen-Ting Yeh, Quentin Roy, Antony Albert Raj Irudayaraj, and Daniel Vogel. 2020. Expanding Side Touch Input on Mobile Phones: Finger Reachability and Two-Dimensional Taps and Flicks using the Index and Thumb. *Proc. ACM Hum.-Comput. Interact.* 4, ISS, Article 206 (Nov. 2020), 20 pages. doi:10.1145/3427334

[77] Hyunjin Yoo, Jungwon Yoon, and Hyunsoo Ji. 2015. Index Finger Zone: Study on Touchable Area Expandability Using Thumb and Index Finger. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct* (Copenhagen, Denmark) *(MobileHCI '15)*. Association for Computing Machinery, New York, NY, USA, 803–810. doi:10.1145/2786567.2793704

[78] Mehrshad Zandigohar, Mo Han, Mohammadreza Sharif, Sezen Yağmur Günay, Mariusz P. Furmanek, Mathew Yarossi, Paolo Bonato, Cagdas Onal, Taşkın Padır, Deniz Erdoğmuş, and Gunar Schirner. 2024. Multimodal fusion of EMG and vision for human grasp intent inference in prosthetic hand control. *Frontiers in Robotics and AI* 11 (Feb. 2024). doi:10.3389/frobt.2024.1312554

[79] Cheng Zhang, Anhong Guo, Dingtian Zhang, Yang Li, Caleb Southern, Rosa I Arriaga, and Gregory D Abowd. 2016. Beyond the touchscreen: an exploration of extending interactions on commodity smartphones. *ACM Transactions on*

Interactive Intelligent Systems (TiiS) 6, 2 (2016), 1–23.
[80] Li Zhang, Huidong Bai, Mark Billinghurst, and Weiping He. 2020. Is This My Phone? Operating a Physical Smartphone in Virtual Reality. In *SIGGRAPH Asia 2020 XR* (Virtual Event, Republic of Korea) *(SA '20)*. Association for Computing Machinery, New York, NY, USA, Article 12, 2 pages. doi:10.1145/3415256.3421499
[81] Xiang Zhang, Kaori Ikematsu, Kunihiro Kato, and Yuta Sugiura. 2022. ReflecTouch: Detecting Grasp Posture of Smartphone Using Corneal Reflection Images. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 289, 8 pages. doi:10.1145/3491102.3517440
[82] Fengyuan Zhu, Zhuoyue Lyu, Mauricio Sousa, and Tovi Grossman. 2022. Touching the droid: Understanding and improving touch precision with mobile devices in virtual reality. In *2022 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, 807–816.
[83] Fengyuan Zhu, Mauricio Sousa, Ludwig Sidenmark, and Tovi Grossman. 2024. PhoneInVR: An Evaluation of Spatial Anchoring and Interaction Techniques for Smartphone Usage in Virtual Reality. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 639, 16 pages. doi:10.1145/3613904.3642582
[84] Tamara Zieher and Kathrin Probst. 2024. Usability Optimization for Mobile Menu Design: An Empirical Study of Hand Grips and User Preferences. *Proc. ACM Hum.-Comput. Interact.* 8, MHCI, Article 263 (Sept. 2024), 19 pages. doi:10.1145/3676508

A Post Hoc Results for Main and Interaction Effects

For completeness, we report the main and two-way interaction effects. Given the significant three-way interaction effect, we recognize that the main effects and the two-way interaction effect are conditional and difficult to interpret independently. We used Holm correction.

A.1 Main Effects

A post-hoc test found no significant differences for used for *Task*.

Post-hoc results for *Phone side* are shown in Table 4.

Table 4: Post-hoc comparisons for independent variable *Phone side* and dependent variable *used*. Positive Z-values mean that the first-named level is sig. higher than the second-named. For negative Z-values, the opposite is true. Effect size reported as rank-biserial correlation (r).

Comparison	Z	p-adjusted	r
Back - Bottom	23.1880	<0.001	0.26
Back - Left	18.4655	<0.001	0.21
Back - Right	20.0145	<0.001	0.22
Back - Top	26.6941	<0.001	0.32
Back - Unknown	17.2130	<0.001	0.36
Bottom - Left	-5.1283	<0.001	0.06
Bottom - Right	-3.6134	<0.001	0.04
Bottom - Top	4.6539	<0.001	0.06
Bottom - Unknown	4.5108	<0.001	0.09
Left - Top	9.5983	<0.001	0.12
Left - Unknown	7.3428	<0.001	0.15
Right - Top	8.1642	<0.001	0.10
Right - Unknown	6.5148	<0.001	0.14

Post-hoc results for *Finger* are shown in Table 5.

A.2 Two-Way Interaction Effects

To aid interpretation of the two-way interactions, we plot the mean finger presence with bootstrapped 95% confidence intervals. Specifically, Figure 8 shows *Task* by *Phone side* (collapsed over *Finger*), Figure 9 shows task by *Finger* (collapsed over *Phone side*), and Figure 10 shows *Phone side* by *Finger* (collapsed over *Task*), corresponding to the factors used in the reported models.

Table 5: Post-hoc comparisons for independent variable *Finger* and dependent variable *used*. Positive Z-values mean that the first-named level is sig. higher than the second-named. For negative Z-values, the opposite is true. Effect size reported as rank-biserial correlation (r).

Comparison	Z	p-adjusted	r
L1 - L2	-10.5862	<0.001	0.17
L1 - L3	-7.8819	<0.001	0.13
L1 - L4	-4.3311	<0.001	0.08
L1 - LPa	-4.7819	<0.001	0.08
L1 - R2	-14.2798	<0.001	0.24
L1 - R3	-11.1138	<0.001	0.18
L1 - R4	-12.7614	<0.001	0.22
L1 - R5	-6.8926	<0.001	0.11
L1 - RPa	-12.9606	<0.001	0.21
L2 - L4	5.3882	<0.001	0.10
L2 - L5	6.8766	<0.001	0.13
L2 - LPa	5.5571	<0.001	0.10
L2 - R1	9.7250	<0.001	0.17
L2 - R2	-3.5364	0.0097	0.06
L2 - R5	3.5364	0.0093	0.06
L3 - L5	4.4356	<0.001	0.08
L3 - R1	7.1359	<0.001	0.12
L3 - R2	-6.1255	<0.001	0.11
L3 - R3	-3.0943	0.0434	0.05
L3 - R4	-5.1649	<0.001	0.09
L3 - RPa	-4.8625	<0.001	0.08
L4 - R1	3.7807	0.0041	0.07
L4 - R2	-8.7223	<0.001	0.16
L4 - R3	-5.8645	<0.001	0.11
L4 - R4	-7.6957	<0.001	0.15
L4 - RPa	-7.5315	<0.001	0.14
L5 - R2	-10.2107	<0.001	0.19
L5 - R3	-7.3529	<0.001	0.13
L5 - R4	-9.1078	<0.001	0.18
L5 - R5	-3.5425	0.0099	0.06
L5 - RPa	-9.0200	<0.001	0.16
LPa - R1	4.1679	<0.001	0.07
LPa - R2	-9.0935	<0.001	0.16
LPa - R3	-6.0623	<0.001	0.10
LPa - R4	-7.9632	<0.001	0.15
LPa - RPa	-7.8305	<0.001	0.13
R1 - R2	-13.2614	<0.001	0.23
R1 - R3	-10.2302	<0.001	0.18
R1 - R4	-11.8927	<0.001	0.22
R1 - R5	-6.1886	<0.001	0.11
R1 - RPa	-11.9984	<0.001	0.21
R2 - R5	7.0727	<0.001	0.12
R3 - R5	4.0416	0.0014	0.07
R4 - R5	6.0580	<0.001	0.11
R5 - RPa	-5.8097	<0.001	0.10

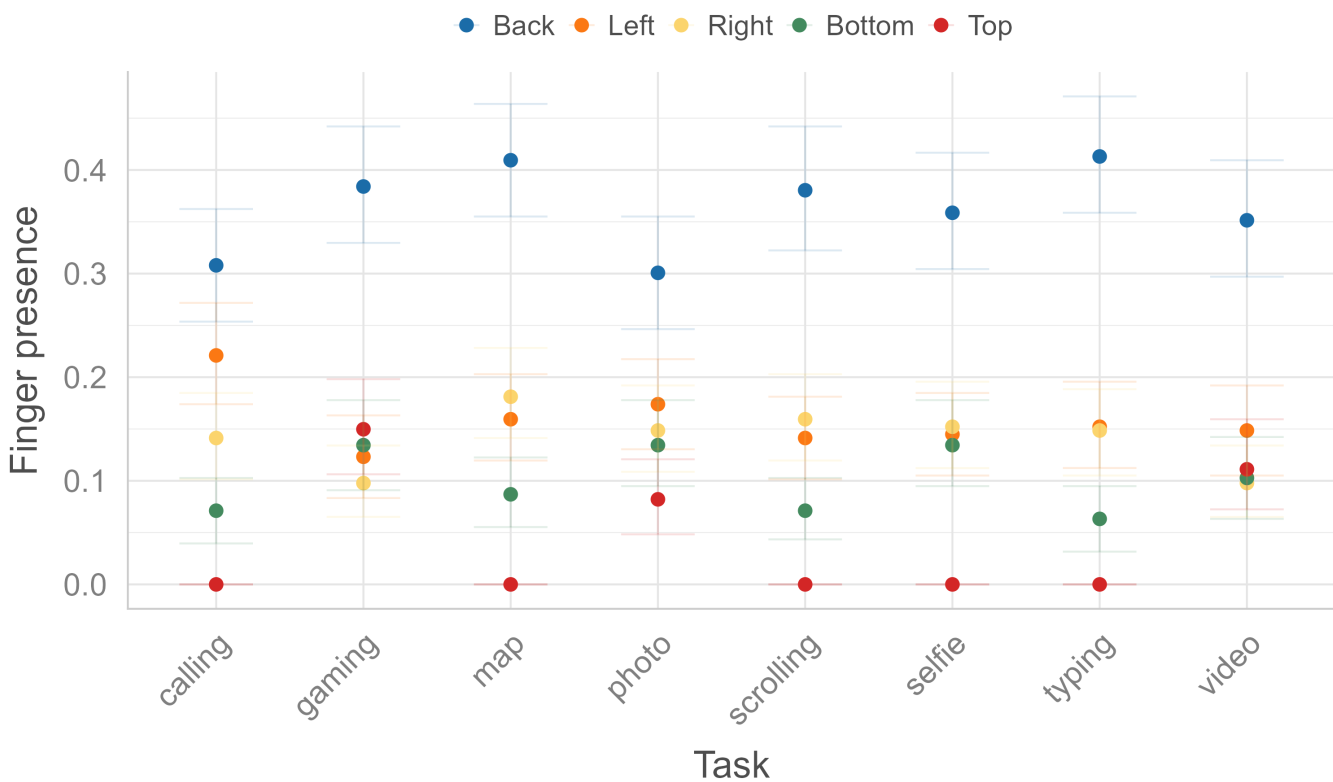


Figure 8: Mean finger presence by task and phone side, collapsed over *Finger*, with bootstrapped 95% confidence intervals.

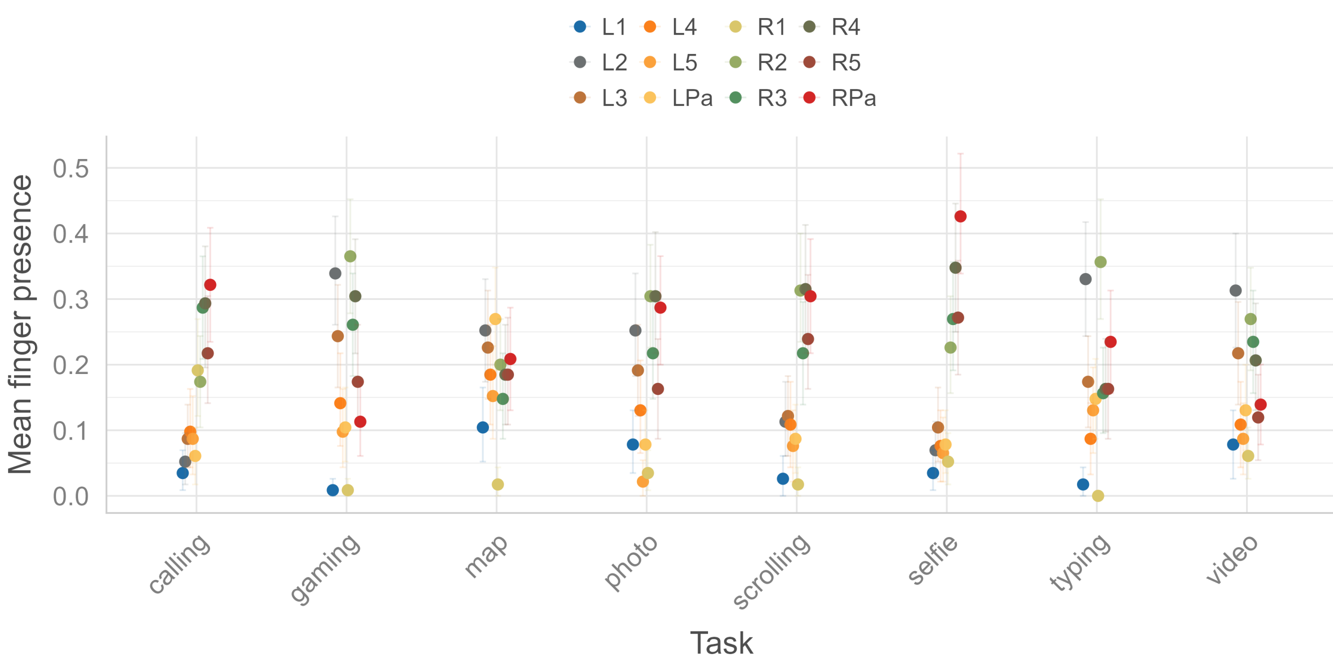


Figure 9: Mean finger presence by task and *Finger*, collapsed over phone side, with bootstrapped 95% confidence intervals.

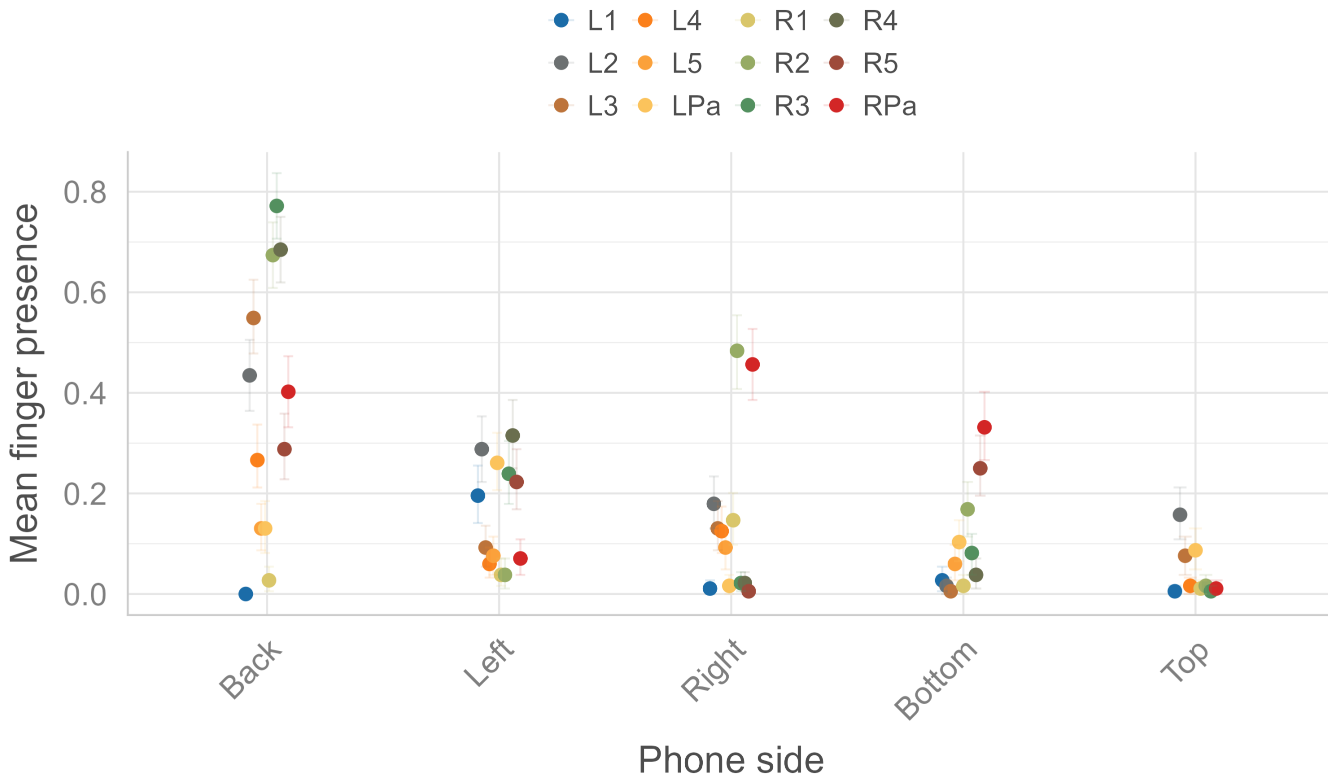


Figure 10: Mean finger presence by phone side and *Finger*, collapsed over task, with bootstrapped 95% confidence intervals.