How to Hold Your Phone When Tapping: A Comparative Study of Performance, Precision, and Errors

Florian Lehmann
LMU Munich
Munich, Germany
florian.lehmann@campus.lmu.de

Michael Kipp
Augsburg University of Applied Sciences
Augsburg, Germany
kipp@hs-augsburg.de

ABSTRACT
We argue that future mobile interfaces should differentiate between various contextual factors like grip and active fingers, adjusting screen elements and behaviors automatically, thus moving from merely responsive design to responsive interaction. Toward this end we conducted a systematic study of screen taps on a mobile device to find out how the way you hold your device impacts performance, precision, and error rate. In our study, we compared three commonly used grips and found that the popular one-handed grip, tapping with the thumb, yields the worst performance. The two-handed grip, tapping with the index finger, is the most precise and least error-prone method, especially in the upper and left halves of the screen. In landscape orientation (two-handed, tapping with both thumbs) we found the best overall performance with a drop in performance in the middle of the screen. Additionally, we found differentiated trade-off relationships and directional effects. From our findings we derive design recommendations for interface designers and give an example how to make interactions truly responsive to the context-of-use.

ACM Classification Keywords
H.5.2 [User Interfaces]: Input devices and strategies.

Author Keywords
Tap; Touch interaction; Mobile device; Handgrip; Smartphone; Performance; Error rate; Precision; Design

INTRODUCTION
Tapping is the most frequent input operation on mobile touch devices such as smartphones, although it suffers from problems like the "fat finger problem", i.e. inaccuracies due to the size of a finger – making it unclear where the actual touch point is located – and the occlusion of the target. This motivated research to understand how users perform a tap [17, 18] and how to correct tap input by systematic offsets to improve accuracy [15] or even complete frameworks which enable developers to use automatic offset correction [5]. Other research focused on practical recommendations, for instance, optimal target sizes for handheld touch devices [32] or introduced models to find out the areas which can be comfortably operated by the thumb in a one-handed grip [3].

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The *performance* of touch operations is of high interest for the design and optimization of user interfaces. Traditionally, Fitts' law studies measure and compare the performance of various input devices [36]. However, recent studies have found that the performance of touch operations depend on a variety of factors that have traditionally not been considered in Fitts' law experiments, like the direction of movement [30] and the specific areas of the screen [31]. Given that smartphones are often held in typical yet varying grips [29, 11] we set out to explore the question how different ways of holding a mobile device influences the performance of tapping.

Handheld devices can be held with either one hand or two hands. They can be held in portrait or landscape orientation. Tapping is usually performed with the thumb or the index finger. Several studies compared the characteristics of different grips, investigating target sizes [32, 33, 34] and automatic touch offset correction [5]. Various studies focused on the task of *text entry* [2], exploring touch offset correction for soft keyboards [13]. Other work suggested finger-specific input methods [9], looked at performance for back-of-the-device interaction [26, 21, 40], or investigated how encumbrance and mobility affects target acquisition in three common grips [29].

Existing work introduced "pre-touch" capabilities, allowing the device to sense hand and finger/s before touch occurs using a self-capacitance touchscreen [16]. Another approach was presented with a prototype incorporating front- and back-of-device touch interfaces and capacitive sensors attached to the edges of the device to classify grip patterns [20]. Other work created adaptive virtual keyboards on tablets based on grip detection, grip was sensed by capacitive sensors attached to the devices [8]. Built-in inertial sensors of smartphones have also been used to automatically detect the user's current grip [14, 26, 28]. Combinations of inertial sensors and capactive sensors for grip recognition were investigated as well [27, 37]. Also, touch input heuristics can be used to infer how a smartphone is held [5, 13, 24]. In light of this research, we can assume that grip-sensing will soon become a widely available and robust feature on mobile devices. Therefore, we argue that touch interaction should be enhanced using grip as an additional parameter for interaction design.

In this paper, we focus on the analysis of taps on smartphone screens in three common grips. We selected three grips reported in prior work [11, 14, 19, 23, 29] to serve as the conditions for our study (see Figure 1): Holding and tapping the phone with the one hand, using the thumb for tapping (1H thumb), holding the phone with one hand and tapping with the other hand, using the index finger (2H index), and holding the phone with both hands in *landscape* orientation, tapping with both thumbs (2H thumbs).

We assume that the characteristics of the grips may have an impact on the performance, precision, as well as on error rates. For instance, we assume for the 1H thumb condition that holding and tapping with the same hand causes inaccuracies. We derived four research questions and conducted an empirical study with 18 participants. We collected data of 51,840 taps in total. The task of the experiment was to tap on appearing targets. We analyzed performance, precision, and errors for the whole screen, screen halves, screen thirds, and quadrants. Additionally, we analyzed trade-off relationships and directional effects.

Our paper makes the following contributions: The comparative analysis of taps on smartphones in three common grips, including screen regions and movement direction. The results show that the two-handed thumbs grip yields the best performance. Taps with the one-handed thumb grip show the worst performance and are also the least precise. Investigating screen quadrants, taps in the two-handed index finger grip are the slowest in the bottom-right quadrant. In terms of error rate, it is safest to tap on the screen half of the dominant hand with the two-handed thumbs grip. Our results also indicate that movement direction influences tap performance, especially in two-handed index finger grip. We derive four design recommendations from our results and give an example of a UI element that adapts to grip.

Our results can be used by interface designers to optimize user interfaces. Moreover, our insights encourage novel methods for adaptive interfaces – moving from merely responsive design to *responsive interaction* where UI elements are aware of the context-of-use and behave accordingly.

RELATED WORK

Basic Research & Input Correction

There is a rich body of research on the tap operation on mobile devices. The research aims to outline the characteristics of touch input [18], to understand inaccuracies [17], and to create models to improve touch accuracy. For instance, Henze et al. [15] conducted a large scale public study using a gamification approach to analyze and correct touch-offsets. Their findings show that taps are systematically skewed. However, a differentiated investigation of grips was not possible because their study was not controlled. Buschek and Alt [5] created TouchML, a publicly available machine learning toolkit for touch offset correction. They showed that their toolkit can improve touch accuracy, considering different aspects, for instance, different target types, hand grips, and the influence of hand sizes. This line of research aims at making the machine automatically correcting touch input. However, we see the need for better interfaces as well, i.e. to provide guidelines for human designers.

Text-Entry

Text entry on soft keyboards was investigated by Azenkot and Zhai [2] in a lab study. Participants had to input text phrases in three different grips (one-handed thumb, two-handed thumbs, and two-handed index finger). They analyzed the data regarding performance, error rates, and touch offsets. Their results reveal that text entry is fastest with two thumbs and slowest with one thumb. In terms of error rates, one handed thumb input showed the least error rate. Analyzing touch offsets, they identified patterns which may be used in keyboard algorithms to correct errors. Such a method was introduced by Goel et al. [13] which built a tool called ContextType, an adaptive text entry system to improve touch screen text entry. Their results showed that the system was able to reduce the error rates for text entry. They agree with Azenkot and Zhai that input operated with two thumbs is the fastest for text entry, but ranked one-handed thumb input prior two-handed index finger input. Regarding accuracy, the index finger was superior and two-handed thumbs input worst. While text entry is a highly relevant task it is also very specific and less suitable to derive generalizable findings, as keyboards cover only parts of the bottom screen. Our work intents to explore taps on the whole screen and for very diverse tasks.

Practical Suggestions

Another branch of research intended to give practical suggestions to design for mobile touch interfaces. Parhi et al. [32] proposed target sizes of 9.2mm for discrete tasks (tapping a single target) and 9.6mm for serial tasks (tapping a sequence of targets) in one-handed thumb use on touchscreen-based handhelds. It is also common to divide screens in cells to give information about the efficiency of certain display regions. Following this approach, Park et al. [33] analyzed such cells considering success rate, error rates, and the so called *pressing convenience* which was subjectively rated by the participants and meant how easily they hit a target. In contradiction to the work by Parthi et al. and Park et al. we focus on providing more general suggestions and to respect also trade-off relationships between screen regions and directional effects.

Performance

Performance of front- and back-of-device- interaction was investigated by Wobbrock et al. [40]. They analyzed drag gesture input in eight different grips. In particular, they examined the input performance of these grips using Fitts' law. As smartphones were not as widespread as today, they built an experimental apparatus where touch input was separated from the display to eliminate any effects on the performance caused by the "fat finger problem" (occlusion and inaccurate touch). Their results show that drag input with the index finger outperformed the thumb in one- and two-handed grips and that input with the index finger is more accurate. Colley and Häkkilä investigated touch interaction on smartphones [9]. They examined touch input for each finger. Generally, they found that any finger can be used effectively for touch input. While they used acquisition time as a performance measure, they did not normalize it with Fitts' law. Nguyen and Kipp [30, 31] measured the performance of translation and rotation touch operations. Their studies focused on movement direction and screen area performance. For one of their studies they used a medium-sized screen (22 inch), divided the display in cells, and compared functional areas (center, edges, corners) [31]. They showed that the bottom-left corner of horizontal displays is the best corner in terms of performance. Also, they showed that the bottom edge outperforms the top as well as the right edge on horizontal displays, using drag operations. For performance analysis we built on the latter approaches to investigate taps on smartphones under a set of different conditions. We used these methods to analyze displays in depth and visualize the findings such that usable insights for interface designers can be derived.

Context-of-use, Adaptive Interfaces

Taps in the context of encumbrance and mobility were explored by Ng et al. [29]. They concentrated on how carrying bags and walking affects target acquisition in three common grips: One-handed thumb, two-handed index finger, and two-handed thumbs. For instance, they showed a drop in accuracy for index finger input to 48.1% when walking. Focusing on the one-handed thumb grip, Bergstrom-Lehtovirta and Oulasvirta introduced a model to provide information about the functional areas [3]. They analyzed the kinematics of the gripping hand and derived a model to predict the screen area that can be comfortably operated in one-handed thumb usage. A system to automatically detect grips was introduced by Goel et al. [14]. They combined touchscreen, built-in inertial sensors, and vibration motors of smartphones to distinguish between one- or two-handed input postures. Moreover, the system was able to infer whether the smartphone was operated with the thumb or the index finger. This way the system was able to enhance interaction, e.g by allowing users to zoom in and to zoom out using pressure input. In the field of adaptive user interfaces Buschek and Alt introduced ProbUI, a GUI framework for Android smartphones [6]. Their framework allows to define declarative gestures, so called bounding behaviours, instead of static bounding boxes. Based on a probabilistic model, gestures are detected and interaction elements adapted. For instance, they presented a slider-widget that starts to bend itself when one-handed thumb input gestures are detected. This way the slider stays within the thumb's reach. With our work we contribute empirical results that allow the development of adaptive interfaces that are aware of the context-of-use.

EXPERIMENT

While a number of possible grips when holding a smartphone have been identified and described in the literature [11, 14, 19, 23, 29], we selected three specific grips as our experimental condition. We deem these grips of particular interest for a variety of interactions (e.g. selection or gaming) but we explicitly exclude the task of text entry. We consider text entry a very specific task in terms of grip and interaction patterns that is already very well researched. Our selected grips are the following three grips (Figure 1):

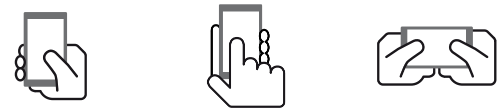

Figure 1. The three conditions in our experiment (left to right): 1H thumb, 2H index, and 2H thumbs.

1H thumb: The one-handed thumb grip is the only technique that can be used with a single hand. The smartphone is held with the dominant hand in portrait orientation, taps are performed with the same hand's thumb. The non-dominant hand is free to perform other tasks. Holding and tapping with the same hand may adversely affect speed and accuracy and may increase fatigue. Since the tapping hand cannot freely move certain screen areas may be better to reach while other areas may be problematic.

2H index: The two-handed index finger grip is the only technique where holding the device and tapping is separated. Taps are performed with the index finger of the dominant hand while the device is held in portrait orientation with the non-dominant hand. The separation of holding and tapping may increase speed and accuracy. Since the tapping hand is free to move in space, performance should be similar in different screen areas.

2H thumbs: The two-handed thumbs grip is the only technique where the device is held with both hands, tapping is performed with both hands (the thumbs), and the device is held in landscape orientation. Distributing holding and tapping on both hands may reduce fatigue. The dominant hand may perform better when compared to the non-dominant hand.

As for screen orientation, each one has typical usage scenarios. Portrait orientation is typically used for reading, browsing through lists, and taking photos. Landscape orientation is typically used for watching videos and photos, playing games, and is generally used more rarely than portrait orientation. In the 2H thumbs condition, we decided for the landscape orientation as we are analyzing taps in general and not in context of a specific task. In contrast, studies focusing on text entry would include the portrait orientation where the smartphone is operated with two hands and both thumbs for typing [2, 7, 13, 22, 35].

Research Questions

Based on our observations and characterization of the conditions, we derive the following research questions:

Q1: For the one-handed thumb condition (1H thumb), does holding and tapping with the same hand make tapping *less precise*?

Q2: For the two-handed index finger condition (2H index), does the separation of holding and tapping make tapping *more precise*?

Q3: For the two-handed index finger condition (2H index), does the separation of holding and tapping make tapping *faster*?

Q4: For the two-handed thumbs condition (2H thumbs), does the screen half of the dominant (right) hand *outperform* the screen half of the non-dominant hand?

Participants
A total of 18 participants (8 females) were recruited via email lists, all right-handed, with an age range of 23 to 31 (M = 25.78, SD = 2.18). Prior experience with smartphones ranged from 3 to 8 years (M = 6.39, SD = 1.38). Participants were compensated with 10 €.

Apparatus
We used a Google Nexus 5X smartphone with a 65×115 mm screen (1080 × 1920 pixels, 423dpi) with Android 7.0. We developed a native Android application for our study. The participants sat on a chair at a table and were instructed to rest their elbows on the table for support.

Figure 2. Participants had to tap on the start zone (white) first and then tap on the target (blue).

Task
The participants had to tap on randomly appearing circular targets under three conditions: 1H thumb, 2H index, and 2H thumbs (Figure 1). For each trial, a start zone (white disc) and a target (blue disc) appeared on a black background (Figure 2). The participants had to tap on the white disc first and then, on the blue disc. Participants were told to tap only if both discs were visible.

They were instructed to tap as quickly and precisely as possible but to keep in mind the trade-off between speed and accuracy. They were told to slow down and tap more accurately if they felt they missed too many targets. Otherwise, they were encouraged to increase their speed if they felt confident that accuracy was high.

When a tap occurred the start zone or target disappeared instantly. Audio-visual feedback was provided for every tap on a target. For a successful tap the background changed to green and faded back to black within 150ms. Additionally, a positive sound for was played. For a missed target, the background changed to red and an error sound was played.

We agree with existing work in our decision to use circular target shapes [15] because target width is the same for every movement direction. Based on work by Parhi et al. [32] we defined two target sizes: 5mm and 10mm.

Distribution of Targets
Targets were distributed evenly across the display to make sure that a balanced amount of distances occurs with respect to the start-target combinations. We pseudo-randomized the target positions by dividing the screen into 16 cells. Corresponding start-target pairs were generated for each combination of two cells and each target size. Exact coordinates were randomized within a cell. This resulted in 15 combinations × 16 cells × 2 target widths = 480 trials per condition and participant.

Questionnaires
Questionnaires were embedded in our app to acquire data about the subjects' demographics and their subjective ratings. Participants had to rate their performance after each condition in terms of difficulty, fatigue, success, and speed. Answers were collected on a five-point scale. The following questions had to been answered:

(1) How difficult was this? (1 = easy, 5 = hard),

(2) How exhausted are you? (1 = low, 5 = high),

(3) How successful were you? (1 = low, 5 = high),

(4) How fast were you? (1 = slow, 5 = fast).

Procedure
The participants were tested under lab conditions. An experimenter gave an initial briefing and handed over the smartphone. A running app guided the participants through the study. The participants were told that they could ask the experimenter anytime if something was unclear. The procedure consisted of three steps.

(1) Collection of demographic data: Participants were asked to input their demographic data.

(2) Execution of the experimental task: Prior to each condition, an information screen explained how to perform the task and in which grip to hold the device. After completing half of the trials of a condition, a *pause screen* was displayed. It displayed the performed number of taps per minute and the current error rate. It also encouraged the participants to take a short break, to stretch their hands, and to try to speed up in the second half while keeping their error rate below 20%.

(3) Subjective rating: Once a condition was completed, the participants had to rate their own performance. A whole session for one subject took about 45 minutes. The pause screen – which appeared every 5-6 minutes – caused subjects to use around one minute for a break to reduce fatigue.

Design
We used a within-subject study design with three conditions (1H thumb, 2H index, 2H thumbs) as the independent variables. Two target sizes of 5mm and 10mm were used across conditions. This resulted in 18 subjects × 3 conditions × 2 target widths × 240 target combinations = 25,920 trials. As each trial consisted of two taps, we collected 51,840 taps in total.

For every trial we measured the following data as dependent variables: *Movement time*, the time between two taps, *error rate*, success/failure of the tap, *touch offsets*, the vector between the centroid of a target and the actual coordinates of the touch (centroids have been used in similar work as a measure of touch accuracy [5, 15, 33]). Trial order was randomized and condition order was counter-balanced in a Latin Square design. The latter should ensure that fatigue effects can be ruled out between conditions.

A	**Screen performance across conditions:**				
	Condition 1	*Condition 2*	*z*	*p-Value*	*r*
	2H index (Mdn = 5.87, SD = 0.89)	1H thumb (Mdn = 4.52, SD = 0.62)	3.72	< .001	0.62
	2H thumbs (Mdn = 7.18, SD = 2.34)	1H thumb (Mdn = 4.52, SD = 0.62)	3.72	< .001	0.62
	2H thumbs (Mdn = 7.18, SD = 2.34)	2H index (Mdn = 5.87, SD = 1.89)	3.50	< .001	0.58
B	**Quadrant performance within 2H index:**				
	Quadrant 1	*Quadrant 2*	*z*	*p-Value*	*r*
	BL (Mdn = 5.89, SD = 0.89)	BR (Mdn = 5.57, SD = 0.84)	3.72	< .001	0.62
	TL (Mdn = 6.00, SD = 0.95)	BR (Mdn = 5.57, SD = 0.84)	3.11	< .004	0.52
	TR (Mdn = 5.93, SD = 0.92)	BR (Mdn = 5.57, SD = 0.84)	3.68	< .001	0.62
C	**Screen halves performance within 2H index:**				
	Screen half 1	*Screen half 2*	*z*	*p-Value*	*r*
	Top (Mdn = 5.97, SD = 0.93)	Bottom (Mdn = 5.74, SD = 0.86)	3.15	< .002	0.52
	Left (Mdn = 5.94, SD = 0.92)	Right (Mdn = 5.80, SD = 0.87)	2.28	< .03	0.38
D	**Screen thirds performance within 2H thumbs:**				
	Screen third 1	*Screen third 2*	*z*	*p-Value*	*r*
	Left (Mdn = 7.42, SD = 2.61)	Center (Mdn = 6.61, SD = 2.48)	3.72	< .001	0.62
	Right (Mdn = 7.64, SD = 2.02)	Center (Mdn = 6.61, SD = 2.48)	2.85	< .006	0.48
E	**Screen thirds error rate within 2H thumbs:**				
	Screen third 1	*Screen third 2*	*z*	*p-Value*	*r*
	Center (Mdn = 11.46, SD = 5.24)	Left (Mdn = 13.06, SD = 3.79)	2.46	< .03	0.41
	Right (Mdn = 9.60, SD = 2.85)	Left (Mdn = 13.06, SD = 3.79)	3.03	< .004	0.50
F	**Touch offset length in mm across conditions:**				
	Condition 1	*Condition 2*	*z*	*p-Value*	*r*
	2H index (Mdn = 0.68, SD = 0.24)	1H thumb (Mdn = 0.94, SD = 0.21)	2.81	< .007	0.47
	2H thumbs (Mdn = 0.77, SD = 0.17)	1H thumb (Mdn = 0.94, SD = 0.21)	3.51	< .001	0.58

Table 1. Results of pairwise comparisons in terms of performance and touch offset lengths. Calculated with a Wilcoxon signed-rank test and the Bonferroni-Holm correction applied. Taps are fastest in the 2H thumbs condition, followed by 2H index, and 1H thumb (A). Within the 2H index condition, taps are slowest in the bottom right quadrant (B). Comparing the screen halves in the 2H index condition, taps are faster in the top screen half than in the bottom, and faster in the left screen half than in the right (C). Taps are slowest in the center third of the screen in the 2H thumb condition (D). In the 2H thumbs condition it is most error-prone to tap in the left third of the screen (E). Taps are generally less accurate in the 1H thumb condition (F).

RESULTS

We analyzed the whole screen, screen halves and quadrants in terms of performance, error rate, and touch offsets. Additionally, we analyzed the screen thirds in the 2H thumbs condition. In preparation, we divided the display into 36 cells (6 columns, 6 rows) and calculated the results for each cell. We decided on these divisions, similar to [31], to arrive at generalizable results and practical guidelines.

We collected data of a total of 25,920 trials resulting in 51,840 taps, as each trial consisted of two taps. Performance was calculated for successful trials only, using the target of a trial (22,810 data points). Touch offsets included all taps except for "accidental" taps. Accidental taps are defined as taps exceeding a distance threshold from the target border (accident rate of 0.21%, resulting in 51,732 valid data points). The outlier threshold was computed for each condition based on the mean and standard deviation of the touch offsets ($M + 3 \times SD$), resulting in 4.99mm for 1H thumb (M = 1.86, SD = 1.04), 4.59mm for 2H index (M = 1.73, SD = 0.96), and 4.69mm for 2H thumbs (M = 1.76, SD = 0.97).

Since our data did not fit the normal distribution in several cases (Shapiro-Wilk test), we decided to rely on non-parametric tests for analysis. We used the Friedman test to test for significant differences between the samples. When significant differences were found, we used the Wilcoxon signed-rank test with Bonferroni-Holm correction applied for post-hoc analysis. Effect sizes were calculated for pairwise comparisons. Our approach follows Wobbrock and Kai [39] and we consistently applied this throughout our analysis so we will not mention the tests in each result. Each test was computed with a sample size of n=18.

Performance

Performance was measured as *throughput* (TP) via the mean of means, as proposed by Soukoreff and MacKenzie [36]:

$$TP = \frac{1}{y}\sum_{i=1}^{y}\left(\frac{1}{x}\sum_{j=1}^{x}\frac{IDe_{ij}}{MT_{ij}}\right) \quad (1)$$

where y is the number of subjects, and x represents the trials per subject. The equation is an adapted version of Fitts' law [12], a measure to normalize performance and make it comparable across conditions. It incorporates the difficulty of the trials as the *effective index of difficulty* (IDe) and the mean time of all trials as *movement time* MT_{ij}.

The calculation of the IDe relies on the Shannon formulation [25] to ensure positive values:

$$IDe = \log_2\left(\frac{D}{We}+1\right) \tag{2}$$

where We is the *effective target width*, as proposed by Crossman [10, 38]. Effective distance De was not computed as this is optional [36].

$$We = SD_{\mathrm{xy}} \times 4.133 \tag{3}$$

SD_{xy} is the standard deviation of tap coordinates relative to a target. We computed We for both target sizes. Since we used a circular target shape, We is equal in any movement direction. The effective target width for 5mm targets was 5.55mm, for 10mm targets 9.29mm.

Comparing screens: Differences in performance on the whole screen were significant across conditions χ^2 (2) = 32.44, $p < 0.001$. Pairwise comparisons were significant in all cases (see Table 1 A). Tap performance in the 2H thumbs condition is superior to the other conditions. Taps in the 1H thumb condition are slowest. Differences are also visualized as *heatmaps* in Figure 3 where dark red indicates high performance (throughput).

Comparing quadrants: Comparing the quadrant performance in the 1H thumb condition, differences were statistically significant χ^2 (3) = 13.27, $p < 0.005$. Taps in the the top-right quadrant (Mdn = 4.54, SD = 0.69) outperformed the top-left quadrant (Mdn = 4.51, SD = 0.67) Z = 3.07, $p < 0.007$, r = 0.51. All other comparisons were not significant in the 1H thumb condition. In the 2H index condition, differences between quadrant performances were also significant χ^2 (3) = 23.53, $p < 0.001$. The results indicate that taps in the bottom-right quadrant are slowest (see Table 1 B).

Comparing the quadrants across conditions, we found no differences to the ranking of the whole-screen performance.

Comparing movement between quadrants: In terms of performance, we also compared the movement between quadrants. For this, we summarized performance of trials which started within a given quadrant and ended in one of the other quadrants. Taps were analyzed for horizontal, vertical, and diagonal directions. For instance, in the 2H index condition, if the start target was placed in the bottom-left quadrant and the end-target in the top right quadrant, the trial was added to the diagonal direction from the bottom-left quadrant the to top-right quadrant (BL to TR).

In the 1H thumb condition, differences were significant χ^2 (11) = 96.57, $p < 0.001$. Taps with an upward movement

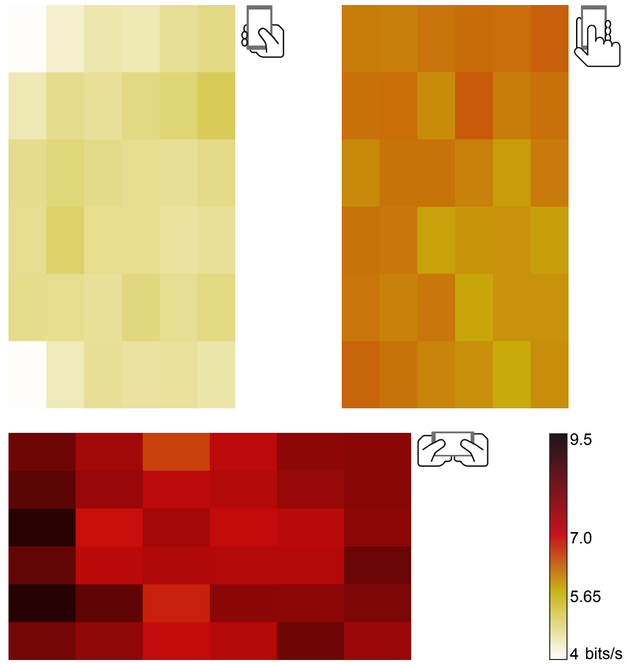

Figure 3. Performance heatmaps of all conditions; dark red indicates high performance (high throughput).

direction are faster on the right screen half (BR to TR; Mdn = 5.01, SD = 0.76) compared to the left screen half (BL to TL; Mdn = 4.74, SD = 0.68) Z = 3.59, $p < 0.003$, r = 0.59.

Differences within 2H index condition showed significance χ^2 (11) = 125.2, $p < 0.001$. Comparing the movement directions on the left as well as on the right screen half, results were significant. Taps with a upward movement direction (BL to TL; Mdn = 6.47, SD = 1.06) were faster than those with a downward direction (TL to BL; Mdn = 5.96, SD = 0.94) Z = 3.07, $p < 0.04$, r = 0.52 on the left screen half. On the right screen half, taps with an upward direction (BR to TR; Mdn = 6.47, SD = 0.86) were also faster than those with a downward direction (TR to BR; Mdn = 5.84, SD = 0.93) Z = 3.07, $p < 0.04$, r = 0.51.

In the 2H index condition, diagonal trials in the downward direction were faster when starting in the top-right quadrant (TR to BL; Mdn = 6.27, SD = 0.89) than in the top-left quadrant (TL to BR; Mdn = 5.79, SD = 0.83) Z = 3.59, $p < 0.002$, r = 0.60. In the diagonal upward direction, taps were faster from the bottom-left to the top right (BL to TR; Mdn = 6.80, SD = 1.04), than from the bottom-right to the top-left (BR to TL; Mdn = 6.43, SD = 0.80) Z = 3.55, $p < 0.003$, r = 0.59.

Comparing screen halves: Differences between the screen halves were significant for the 1H thumb χ^2 (3) = 11.33, $p < 0.02$ and the 2H index condition χ^2 (3) = 16.33, $p < 0.001$.

Taps within the 1H thumb condition were faster on the right screen half (Mdn = 4.54, SD = 0.65) than on the left screen half (Mdn = 4.43, SD = 0.61) Z = 2.81, $p < 0.01$, r = 0.47.

Within the 2H index condition taps were faster on the top half compared to the bottom half. Also, taps are faster on the left half, compared to the right half (see Table 1 C).

Comparing the halves across conditions, we found no significant differences.

Comparing screen thirds: Differences between screen thirds in the 2H thumbs condition were significant χ^2 (2) = 24.11, $p < 0.001$. Taps in the center of the screen were the slowest within 2H thumbs (see Table 1 D).

Error Rate

Errors are defined as taps that were outside the target circle. They were assigned to the quadrant in which the corresponding target had been displayed. Error rates are visualized as *heatmaps* in Figure 4.

Comparing screens: Error rates across conditions were significant χ^2 (2) = 13.78, $p < 0.002$. Taps in the 2H index condition (Mdn = 8.57, SD = 3.43) are safer than in the 1H thumb condition (Mdn = 13.92, SD = 4.79) Z = 3.59, $p < 0.001$, r = 0.60. We found no significant results comparing 1H thumb with 2H thumbs or the 2H index with the 2H thumbs condition.

Comparing quadrants: Significant differences were found for the 2H index condition χ^2 (3) = 8.07, $p < 0.05$ and the 2H thumbs condition χ^2 (3) = 12.6, $p < 0.006$.

In the 2H index condition, taps are less error-prone in the bottom-left quadrant (Mdn = 7.22, SD = 3.33) compared to taps in the top-right quadrant (Mdn = 10.12, SD = 3.97) Z = 3.16, $p < 0.005$, r = 0.53.

Comparing the quadrants in 2H thumb condition, taps in the bottom-left (Mdn = 13.22, SD = 4.58) are more error-prone than in the bottom-right quadrant (Mdn = 10.00, SD = 3.05) Z = 2.93, $p < 0.02$, r = 0.49.

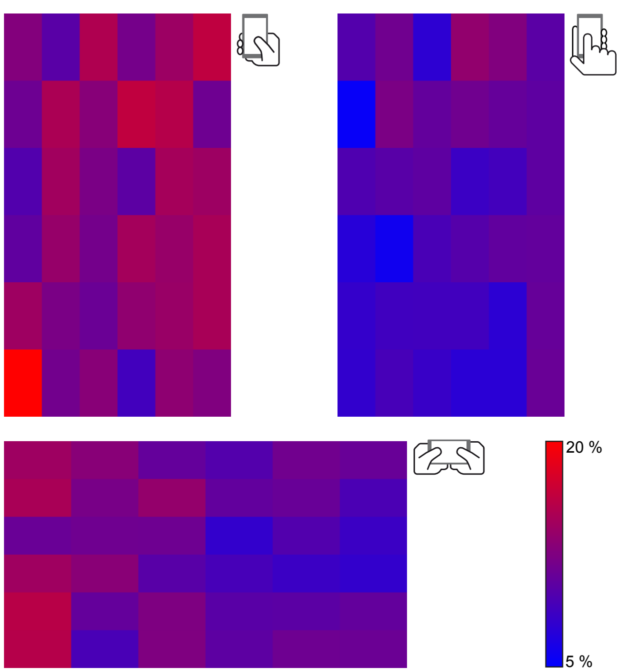

Figure 4. Error heatmaps of all conditions.

Comparing screen halves: Comparing screen halves within conditions, 2H index showed significant results χ^2 (3) = 8.07, $p < 0.05$ as well as 2H thumbs χ^2 (3) = 12.6, $p < 0.006$. Comparisons within 1H thumb showed no significant differences.

Taps in the 2H index condition are safer in the bottom half (Mdn = 7.90, SD = 3.27) compared to the top half (Mdn = 9.45, SD = 3.99) Z = 2.33, $p < 0.04$, r = 0.38. Also, it is safer to tap on the left half (Mdn = 7.76, SD = 3.65) compared to the right half (Mdn = 8.94, SD = 3.50) Z = 2.02, $p < 0.05$, r = 0.34.

In the 2H thumbs condition taps in the right half (Mdn = 9.75 SD = 3.28) are safer than in the left half (Mdn = 12.85, SD = 4.076) Z = 2.76, $p < 0.009$, r = 0.46.

Comparing screen thirds: Within the 2H thumbs condition, there were significant differences between screen thirds in terms of error rate χ^2 (2) = 10.11, $p < 0.007$. Taps on the left screen third are the most unsafe in a pairwise comparison (see Table 1 E).

Precision

To measure precision we looked at the deviation of the actual tap position to the center of the target circle. For each tap, the *touch offset* is defined as the vector from the target center to the tap position. We averaged the sum of all resulting offset vectors per cell. Taps with a distance greater than 4.99mm (1H thumb), 4.59mm (2H index), and 4.69mm (2H thumbs) were considered outliers and were excluded from our analysis (as explained above).

Comparing screens: Touch offsets show significant differences across conditions χ^2 (2) = 12.44, $p < 0.002$. People are less precise to tap in the 1H thumb condition as shown by a pairwise comparison of touch offsets between conditions (see Table 1 F). The effect is also visible in Figure 5.

Comparing quadrants: Quadrants within the 1H thumb condition showed significant differences χ^2 (3) = 11.27, $p < 0.02$. Differences were not significant within the other conditions.

In the 1H thumb condition taps in the top-left quadrant (Mdn = 0.79, SD = 0.23) are more precise than in the top-right (Mdn = 1.08, SD = 0.37) Z = 3.55, $p < 0.001$, r = 0.59.

Comparing screen halves: Screen halves in 1H thumb condition showed significant differences χ^2 (3) = 8.13, $p < 0.05$. Pairwise comparisons indicated that people are more precise when tapping on the left half (Mdn = 0.85, SD = 0.18) than on the right half (Mdn = 1.10, SD = 0.30) Z = 2.98, $p < 0.01$, r = 0.50.

Comparing screen thirds: Screen thirds showed no significant differences within the 2H thumbs condition.

Questionnaire

Results of the subjective rating showed significant differences for difficulty χ^2 (2) = 14.46, $p < 0.001$, fatigue χ^2 (2) = 12.93, $p < 0.002$, and success χ^2 (2) = 13.3, $p < 0.002$.

	Difficulty		Fatigue		Success		Speed	
Cond.	*Mdn*	*SD*	*Mdn*	*SD*	*Mdn*	*SD*	*Mdn*	*SD*
1H Th.	4	0.55	4	0.83	2	1.04	2.5	0.96
2H Idx.	2	1.2	3	0.87	4	0.78	4	0.92
2H Th.	2	1	3	1.2	3.5	1.04	4	1.15

Table 2. Results of the questionnaire. Participants rated their performance for each condition.

	Condition 1	Condition 2	z	p-Value	r
Difficulty	1H thumb	2H index	2.37	< 0.04	0.40
	1H thumb	2H thumbs	3.35	< 0.002	0.56
Fatigue	1H thumb	2H index	2.32	< 0.05	0.39
	1H thumb	2H thumbs	2.97	< 0.01	0.50
Success	1H thumb	2H index	2.91	< 0.001	0.49
	1H thumb	2H thumbs	2.51	< 0.02	0.42

Table 3. Results of the pairwise comparison of the subjective rating across conditions. Calculated with the Wilcoxon signed-rank test and Bonferroni-Holm correction applied. Medians and standard deviations as seen in Table 2.

The 1H thumb condition is perceived as the most difficult, most exhausting, and least successful compared to the other conditions as revealed by post-hoc analysis. For details, see Tables 2 and 3.

DISCUSSION

How do you best hold your phone for tapping? And where on the screens do you best place critical UI elements? Our results give a differentiated picture, visually summarized in Table 4.

The 1H thumb grip is a frequently used posture because it only requires one hand. This comes at a price: This condition yields the worst performance (Q1). Why? First, the smartphone is held with the same hand that performs the tapping. Second, due to screen size and anatomy it is hard to reach targets near the edges and corners. The thumb has to be stretched or flexed to reach the targets properly [4]. We observed that participants had trouble acquiring targets in the top-left corner. Many performed a supportive (but possibly distracting) device-to-thumb motion to better reach these targets. Eardley et al. [11] systematically explored this effect. They identified as major factors the phone size and the distance to the target: The larger a device and the smaller the operating hand, the greater tilt and rotation will be. Due to greater tilt and rotation it might be beneficial to add stability by holding the smartphone with the non-dominant hand and to use the thumb more freely for input [11]. Putting the little finger below the bottom edge of the device keeps it from dropping out of the hand [23] and may add additional stability. Work by Le et al. [21] outlined the comfortable area for one handed thumb input which can further guide for the placement of interaction elements. Another explanation for imprecision is the "fat finger problem" [15], i.e. the thumb (partially) occludes the target and has a larger contact area on the touch surface. Users cannot not see the target clearly and often have a different conception of where the actual contact point is [17]. So we can answer Q1 conclusively: Operating the smartphone with one hand and the thumb results in the worst precision.

While it is clear that this grip is problematic, we can differentiate the performance problem to allow designers to alleviate the effect by good design. We found that performance in the right screen half is better (also in the upper-right quadrant). On the other hand, precision seems to be better on the left screen half (also in the upper-left quadrant). UI designers can take this performance-precision trade-off into account. Also, it is known that the thumb movement in the direction toward the palm (or in the opposite direction) is difficult to achieve and should be avoided [4, 19]. This also explains why we found a better performance for upward movements on the right screen half than on the left screen half. The movement into the top-right quadrant is more natural, as it requires less stretching or flexing of the thumb or executing a supportive motion to acquire targets. Even in the subjective ratings, the 1H thumb grip is perceived as the most difficult, the slowest, and least successful condition. It shows that users are aware of the trade-off between loss of performance and the convenience of operating the phone with a single hand.

The 2H index grip has some interesting properties: Taps in the top screen half and in the left screen half generally perform better and there is a particularly bad performance in the bottom-right quadrant. Mobile phones are generally held more at the bottom half. The palm and fingers of the holding hand that are visible at the edges may be distracting for taps that occur near them. Since all participants in our study were right-handed this may support the assumption: The participants held the smartphone with the left hand, visible fingertips on the bottom-right smartphone edge may distract from input on the bottom-right edge of the display. The visualization of the error rates indicates also a higher rate on the right edge of

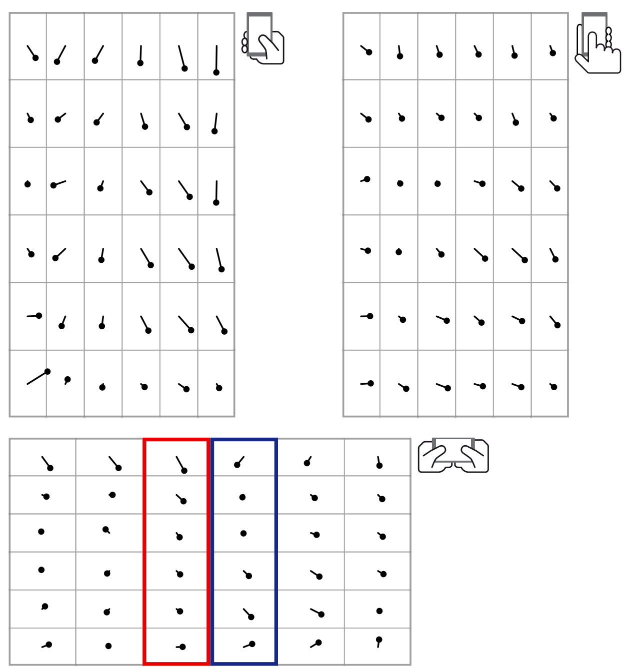

Figure 5. Touch offset vector fields of all conditions (lengths: 0.02mm - 1.26mm). Roughly horizontally mirrored touch offsets of the screen halves under the 2H thumbs condition, with the exception of the two middle columns (red and blue).

the display (see Figure 4). This explanation could be complementary to those by Avrahami [1] who reported a decrease in performance for edge targets in general. He also discussed visual interference: Separating the edge and target might be cognitively more demanding. Hence, the visible fingertips on the right may add additional distraction. In contrast to the low performance on the bottom half, taps were safer in comparison to the top half when tapping with the index finger. This phenomenon might be explained by existing work [4, 18]: The contact area between the touch surface and the finger is used to compute its centroid which is in turn interpreted as the intended tap. Taps with the index finger are performed almost perpendicular to the touch surface which results in a minimal contact area. For the hand that operates the input, we assume a resting position right above of one of the bottom corners of the smartphone. In our case, the bottom right corner. This may have led participants to execute taps more perpendicular with the index finger on the bottom half. The analysis of the movement directions showed faster taps for the upward than the downward direction on the left, as well as on the right screen half. For diagonal movements we assume anatomical characteristics to be responsible for performance effects. Interactions on the diagonal axis between the bottom-left and the top-right quadrant performed well. This may relate to the kinematic chain which is used for input [31]. For right-handed users the execution of this movement direction may require less effort. For the movement between the bottom-right and the top-left quadrant more stretching and flexing of the wrist joint must be performed. If the arm is not supported by resting on a surface, the movement would also include the shoulder joint into the kinematic chain, most probably resulting in increased fatigue.

In the 2H thumbs grip the center of the the screen performs less well and especially the left third is quite error-prone. In a visual analysis of the touch offset angles (Figure 5), the 2H thumbs condition showed a nearly mirrored characteristic of the screen halves. However, the third column (red) is an exception, as it is not mirrored along the x-axis relative to the fourth column (blue). We observed that subjects tend to tap more often with the thumb of the dominant (right) hand, even when a target is displayed on the opposite screen half. In terms of performance, we could not find a difference between the left and the right screen halves. This negatively answers Q4 where we wondered whether the right screen half (of the dominant hand) would yield a higher performance. However, the right screen half is still recommended (for right-handed users) as it has a lower error-rate and because it may avoid the low-performance middle section. For more specific tasks, e.g. text entry, it may be preferable to use the two-handed thumbs grip in *portrait* orientation as reported by Shirazi et al. [35]. They have also showed that user briefly change between orientations when performing text input and landscape orientation is dominantly used for media-related applications.

Comparing performance across conditions, the two-handed thumbs (2H thumbs) grip was superior overall, even compared to the two-handed index (2H index) grip. This is the only major difference between the two conditions. It negatively answers our questions Q2 and Q3: Our assumption that the separation of holding the device and tapping increases performance (Q2) and precision (Q3) *in general* is wrong. Instead, one has to *differentiate* between screen regions when comparing grips (Table 4). In terms of whole-screen performance, we found the following order: 2H thumbs is fastest, followed by 2H index and 1H thumb. This is in agreement with work by Azenkot and Zhai [2].

Our analysis of touch offsets differs from related work [5, 15]. For instance, touch offsets at the edges of the display tend not to point to the center of the screen (see Figure 5). Also, the resulting vectors fields differ radically between the three grips. Therefore, our results clearly show that the grip has to be taken into account when trying to automatically correct user touch offset to increase touch accuracy [15, 18].

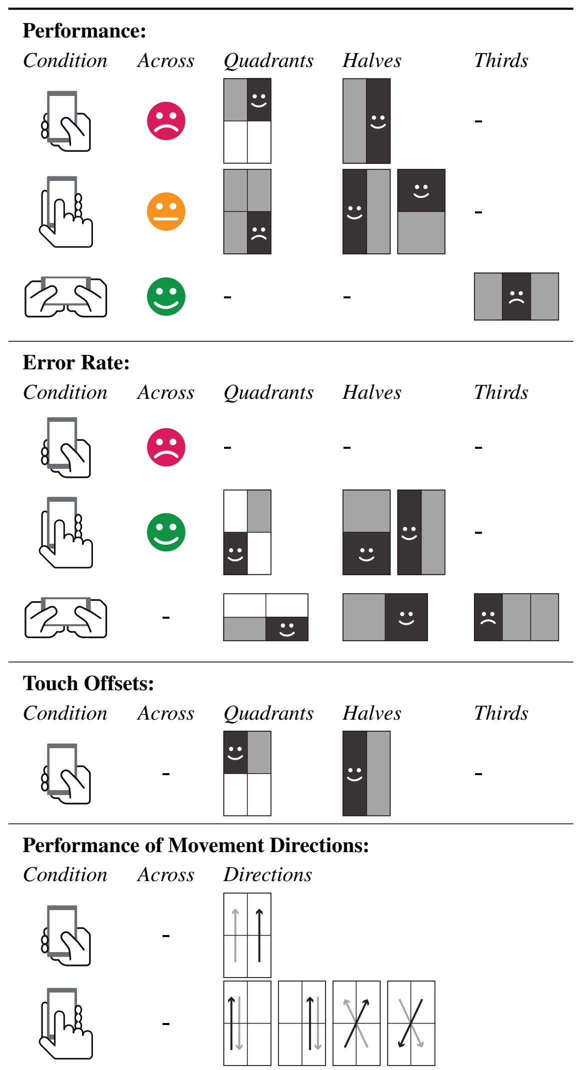

Table 4. Visual overview of our results. Displayed icons visualize significant results from comparisons. Dashes imply that no significant result was found. Smileys in *Across* column visualize ordered results of comparisons between conditions. Happy smileys indicate a significantly "positive" result for an area (high performance, low error rate, small touch offset). Sad smileys indicate a "negative" result. Grey areas are those that the significant area was compared against. For movement direction the dark arrow indicates significantly better performance in comparison with the light grey arrow.

DESIGN RECOMMENDATIONS

Our results give a differentiated picture of performance, precision and errors. Depending on the grip, different screen regions are better in terms of these three measures. We derived four design recommendations to guide UI designers or automatic responsive interaction:

- *High-performance applications*: Prefer the top right quadrant in portrait orientation, avoid the middle section in landscape orientation.
- *Safety-sensitive applications*: Discourage the use of thumb input, focus on the lower left quadrant in portrait orientation, prefer the right half in landscape orientation.
- *High-precision tasks*: Give preference to the top left quadrant in portrait orientation.
- *Control motions (e.g. sliding, scrolling)*: Prefer upward motions over downward motions in portrait orientation.

How could an automatic adjustment of a UI depending on grip, in the sense of a *responsive interaction*, look like? As a demonstration of how to use our results (similar to [11]) we suggest a pull-out menu which adjusts to the respective grip (see Figure 6). The design is derived from our visual summary seen in Table 4 and respects our findings for performance and error rates: Interaction elements should be placed in display regions that yield high performance and few errors.

We hope that UI designers will come up with many more UI variants that feature responsive interaction.

CONCLUSION & FUTURE WORK

We explored how the way one holds a smartphone impacts tapping performance. Three grips were considered (Figure 1), following previous work on handhelds [11, 14, 19, 23, 29]: One-handed thumb portrait (1H thumb), two-handed index finger portrait (2H index), and two-handed thumbs landscape (2H thumbs). Holding the smartphone with two hands and tapping with both thumbs (2H thumbs), taps are fastest. In contrast, taps are slowest and also least precise when the smartphone is held with the one hand and taps are performed with the thumb of the same hand (1H thumb). However, this particular grip is highly common and popular because the other hand is free to perform other tasks like carrying a bag, opening a door, etc.

We summarized our results visually in Table 4. We analyzed the screen quadrants, thirds, and halves. Analyzing the screen halves in one-handed thumb grip (1H thumb) showed that taps are the fastest on the right screen half. This region is reached without stretching or flexing the thumb. In the two-handed index finger grip (2H index), taps were slowest in the bottom right quadrant. The fingertips of the holding hand may act as distractors near the bottom right edge. Tapping with the index finger is faster on the diagonal axis between the bottom left and top right quadrants, compared to the other diagonal. Again we assume that for anatomical reasons it is easier to execute this movement. Fewer joints have to be activated, stretched or flexed. Tapping in the two-handed thumbs grip (2H thumbs), it is the safest to tap on the right screen half. In the two-handed index finger grip (2H index), it is the safest to tap on the bottom half. We also found a speed-precision trade-off in the one-handed thumb condition and a speed-error trade-off in the two-handed index-finger condition. Subjectively, participants were aware of how well they performed. They rated their taps under the one-handed thumb condition (1H thumb) as most difficult, slowest, and least successful overall.

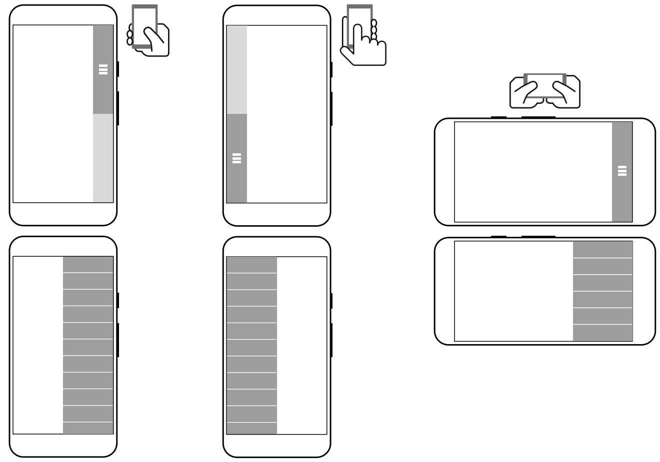

Figure 6. Possible "grip responsive" pull-out menu, based on the results from Table 4. Left to right: 1H thumb, 2H index, 2H thumbs. The upper image shows the collapsed menu. When touching/pulling the menu icon, the menu is pulled out as shown in the respective lower image.

Based on our findings, we conclude that a static user interface cannot be optimal for all grips in the same way. Consequently, we see the need for adaptive interfaces. This is made possible by recent advances in detecting the current grip automatically [16, 20]. Adaptive interfaces will consider multiple aspects (e.g. the handedness and the input finger) for the automatic adjustment and optimization of the interface. Work by Goel et al. [14] and Buschek and Alt [6] already showed that adaptive interfaces are feasible on mobile devices. However, when speaking about adaptive interfaces, not only graphical representation of elements should adapt, but also the interaction method, moving from responsive design to *responsive interaction* that is aware of the context-of-use. We see our work as an empirical foundation that enables the development of such responsive interaction and suggested four design guidelines that consider both grip and task execution priority (performance, safety, or precision). We also presented a grip-sensitive pull-out menu as an example of how to apply our findings.

For the future, we plan to explore further aspects that may impact performance, like screen size, relative position and angle. We also plan to analyze the impact of body posture and kinematic chains on performance [31]. Ultimately, a similar methodology of performance analysis should be transferred and applied to in-air (gestural) interaction.

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