

# Tapping Task Performance on Smartphones in Cold Temperature

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We present a study that quantifies the effect of cold temperature on smartphone input performance, particularly on tapping tasks. Our results show that smartphone input performance decreases when completing tapping tasks in cold temperatures. We show that colder temperature is associated with lower throughput and less accurate performance when using the phone in both one-handed and two-handed operations. We also demonstrate that colder temperature is related to higher error rate when using the phone in one-handed operation only, but not two-handed. Finally, we identify a number of design recommendations from the literature that can be considered as a countermeasure to poorer smartphone input performance in completing tapping tasks in cold temperature.

## RESEARCH HIGHLIGHTS

- We report a study investigating the effect of cold temperature on smartphone input performance when completing tapping tasks.
- We demonstrate that input performance when completing tapping tasks on smartphones in cold temperatures result in lower throughput and higher error rate when the device is used in two-handed mode.
- We suggest the use of finger temperature for improving estimation of movement time in Fitts' law formula.
- We provide recommendations on the design and implementation of smartphone interfaces.

*Keywords:* Fitts' law; tapping tasks; smartphone input performance; cold temperature; cold chamber; physiological measurements; ergonomics

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## 1. INTRODUCTION

In this article, we investigate the effect of temperature on smartphone input performance when completing tapping tasks. An increasingly more common scenario in cold climates is for users to interact with their mobile phones in outdoor settings due to the increased ubiquity of these devices (Liu *et al.*, 2014). While touchscreen gloves and capacitive styluses enable users to interact with mobile devices while keeping their hands warm, they have not been widely adopted

due to the low conductivity of touchscreen gloves (Harrington *et al.*, 2015), discomfort during extensive typing (Harrington *et al.*, 2015), and humans' tendency to misplace their stylus (Murphy, 2015). As a result, individuals are likely to use their smartphones with their bare hands in cold outdoor settings, possibly affecting their input performance.

Rich literature exists on how situational factors can impair input on mobile devices, such as motion (Goel *et al.*, 2012; Kane *et al.*, 2008), divided attention (Kane *et al.*, 2009) and

ambient noise (Wobbrock, 2006). However, very little prior work has considered ambient or finger temperature as an inhibiting factor for input on mobile devices, even though it has been shown to significantly affect perceived comfort (Halvey *et al.*, 2012). Specifically, we aim to investigate if ambient and finger temperature affect users' movement time, error rate or throughput during Fitts' law tests on a smartphone. Fitts' law is a model that predicts movement time taken to hit a target based on the difficulty of the target selection task (index of difficulty). The index of difficulty is defined by the target width and the distance to the target (Fitts, 1954).

Our work evaluates users' input performance during interaction with smartphones in a cold environment when completing tapping tasks, and suggests that adjusting the target's effective size can improve performance and reduce errors. Finally, we provide a reformulation of Fitts' law that takes into account finger temperature.

## 2. RELATED WORK

### 2.1. Physiological response to cold temperatures

When exposed to cold temperature, the human body experiences vasoconstriction reaction of skin arteries (Lewis, 1930; Morton and Provins, 1960) in an attempt to preserve body heat by reducing heat loss (Jin *et al.*, 2007). Vasoconstriction reduces blood supply to the skin and extremities (Jin *et al.*, 2007), leading to greater heat loss from fingers (Kunesch *et al.*, 1987; Virokannas, 1996; Holmer *et al.*, 2012) and decreased touch sensitivity in the hand (Phetteplace, 2000). As a result, the dexterity of extremities diminishes, joints become stiffer and muscles lose some of their strength (Phetteplace, 2000). Previous work has shown that when hand skin temperature drops significantly, tasks requiring increased dexterity and less strength suffer a performance drop of up to 60% (Yeshnik, 1988). In general, finger dexterity degrades when the skin temperature drops below 15°C (Havenith *et al.*, 1995), while sensitivity drops rapidly below skin temperatures of 6–8°C (Mills, 1956; Mortons and Provins, 1960).

Two additional factors have been linked to physiological response to cold. First, several studies have reported gender-related and age-related differences. Specifically, females experience accelerated decrease in hand skin temperature (Barteling *et al.*, 1993) and reach lower skin temperatures (Reading *et al.*, 1997) as well as elderly people (Smolander 2002). Second, acclimatization to cold has also been shown to affect physiological response. For instance, in workplaces where hands are exposed to cold, workers develop higher blood flow in their hands (Krog *et al.*, 1960; LeBlanc *et al.*, 1960). Similarly, individuals whose daily work takes place in cold environments have a higher mean finger temperature (Tanaka, 1971), while individuals who lack indoor heating at home experience less cold and discomfort during cold

exposures than those who have indoor heating (Yu *et al.*, 2013). Thus, gender, age and acclimatization need to be controlled in studies investigating physiological response to cold.

### 2.2. Manual dexterity and target selection performance

We hypothesize that cold hands and fingers can severely affect smartphone usage due to decreased manual dexterity. For instance, standardized Pegboard tests show that decreased manual dexterity significantly increases reaction time in manual tasks (Jin *et al.*, 2007). Thus, in our study, we wish to quantify to what extent finger temperature, which affects manual dexterity, also affects finger movement time for target selection on smartphones.

Very little prior work has directly studied the effects of temperature on human–computer interaction performance. Blomkvist and Gard (2000) used a target size in a Fitts' selection task (Fitts, 1954) to investigate the effect of cold hands on desktop input using a mouse, two trackballs (small, large) and a Wacom tablet with two pens (thin and thick). The experiment consisted of four sessions, with one of the sessions performed with cold hands. In that session, participants' hands were immersed into a large bowl with a mixture of snow and water, and kept immersed until the finger skin temperature reached 11°C. The study reported that participants with cold hands performed slower when using trackballs, which require higher finger dexterity, regardless the target size. On the other hand, the use of mouse and pen-on-tablet was not as affected by cold hands. Moreover, women made more errors than men on small target task when gender and target size were tested alone. Finally, the study reports that participants did not trade off error against speed when having their hands cooled, but retained their ambitions to be correct by reducing their pace. This effect was also shown by Gentile (1987).

There is rich ergonomics literature on the effect of cold temperature. Teichner and Kobrick (1955) showed that visual-motor performance is severely impaired in the cold, and does not fully recover in cold temperatures, while cold has been linked to reduced finger dexterity (Morton and Provins, 1960). As a result, we expect that the reduced finger dexterity and motor impairment caused by cold may affect users' ability to operate their mobile devices. Furthermore, we expect holding posture of the device to influence the effect of cold on input performance in completing tapping tasks. The three main holding postures are as follows: one-handed using the thumb, two-handed holding the device with non-dominant hand and using index finger of the dominant hand and two-handed using both thumbs. We decided to use the first two as this enabled us to directly compare two different fingers (index and thumb).

Since cold-induced motor impairment is akin to a temporary disability, it is also helpful to consider the literature on the use of touchscreen technology by motor-impaired

individuals. Such individuals typically find conventional gestures challenging (e.g. swiping, scrolling and tapping), often causing them to refrain from using touchscreen devices altogether (Zhong *et al.*, 2015). Duff *et al.* (2010) and Guerreiro *et al.* (2010) report that motor-impaired individuals make more mistakes than people without disabilities when hitting targets on a touchscreen. Irwin and Sesto (2012) show that users with motor impairments require dwell time for tapping tasks on touchscreens. Therefore, design implications from this area of research can potentially be adapted for users without disabilities when suffering from cold-induced decreases in manual dexterity (Newell and Cairns, 1993).

We report the first study that examines the effect of cooling fingers on users' performance in completing tapping tasks in the context of a Fitts' law. Unlike previous work, we do not cool fingers locally via cold water immersion, but we place our participants in a cold environmental chamber that more accurately emulates exposure to outdoor winter conditions.

### 3. METHOD

#### 3.1. Variables

The study followed a within-subjects experimental design similar to the one reported in Sarsenbayeva *et al.* (2016). The first independent variable was ambient temperature, treated as a continuous (rather than categorical) variable, and was controlled by using two separate rooms for the study: a warm room and a cold chamber. The second independent variable was the finger used for target selection: index finger or thumb. This also directly affects holding posture, since thumb was used in one-handed operation, while the index finger requires two-handed operation. Additional independent variables were introduced by the software used to conduct a 1D Fitts' law test: target amplitude (106, 212, 425 pixels, specifying center-to-center distance between targets), and target width (27, 53, 106 pixels, specifying the width of targets). These two values were scaled by the software such that the widest condition (largest amplitude and width) spans the device's display with minus 10 pixels on each side (MacKenzie, 2015). The Human Sciences ethics committee of our university approved the experimental design.

#### 3.2. Participants

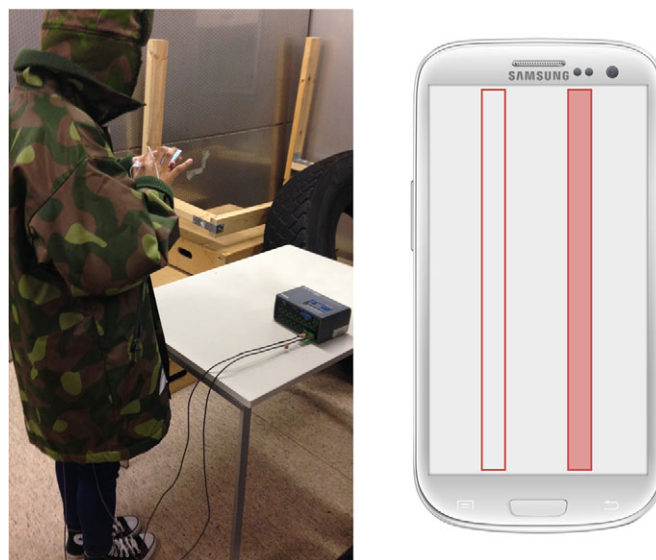
Participants were recruited through mailing lists. Twenty-four participants aged 20–35 years ( $M = 26.2$ ,  $SD = 3.6$ ) enrolled (12 male, 12 female). Gender was balanced since the literature suggests that it affects physiological response to cold (Barteling *et al.*, 1993; Reading *et al.*, 1997). We controlled for acclimatization to cold temperature by ensuring that all participants had lived in cold climates (Northern Scandinavia) for more than a year. Participants were required to have owned a smartphone for more than a year. Participants' clothing was

controlled by instructing them to wear a single layer of trousers, one pair of socks and top garment on the day of the study. During the experiment, every participant was asked to wear additional winter attire provided by us, consisting of a winter jacket and hat (Fig. 1). The participants were asked to not wear gloves nor warm their hands through movement, rubbing or the pockets. Each participant was paid 40€ for participation.

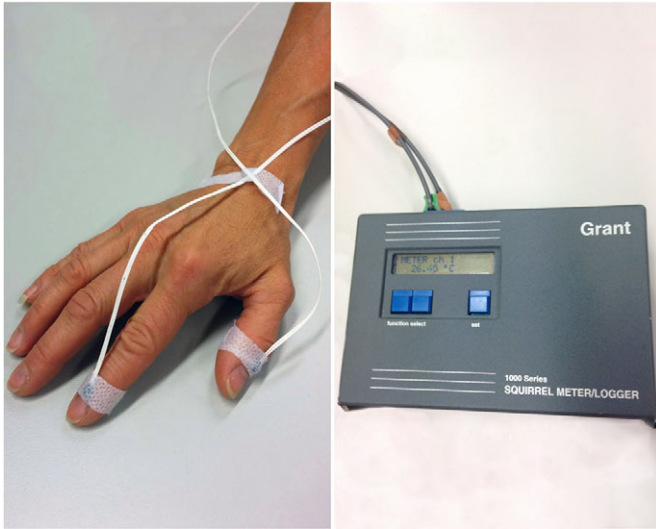
#### 3.3. Apparatus

Participants used a Samsung Galaxy S4 smartphone running Google's Android 4.1 (Jelly Bean) operating system with a 4-inch screen sized  $540 \times 960$  pixels. The FittsTouch Android application by MacKenzie (2015) was used to evaluate touch-based target selection using Fitts' law (Fig. 1). The application was modified to disable the repetition of sequences that contain excessive errors. This was required to ensure that all participants are exposed to cold for equal time periods, thus avoiding excessive cooling and minimizing possible learning effects. Furthermore, vibrotactile and auditory feedback was disabled to avoid distracting the participants during the experiment.

The experiment took place in two adjacent rooms. The warm room had a controlled ambient temperature of  $24^{\circ}\text{C}$ , wind velocity below  $0.1\text{ m/s}$  and humidity of 30–35%. The cold chamber had a controlled ambient temperature of  $-10^{\circ}\text{C}$ , wind velocity below  $0.1\text{ m/s}$  and humidity of 70–75%. Finger temperature was measured using two thermistors (YSI 427, YSI, Inc. USA) attached to the index finger and thumb of each participant's dominant hand, just below the nail. Thermal data were logged every 10 s using a mobile battery-powered Grant Squirrel meter/logger series 1000 (Fig. 2).



**Figure 1.** Participant performing the test with index finger inside the cold chamber and a screen of the FittsTouch Android application.

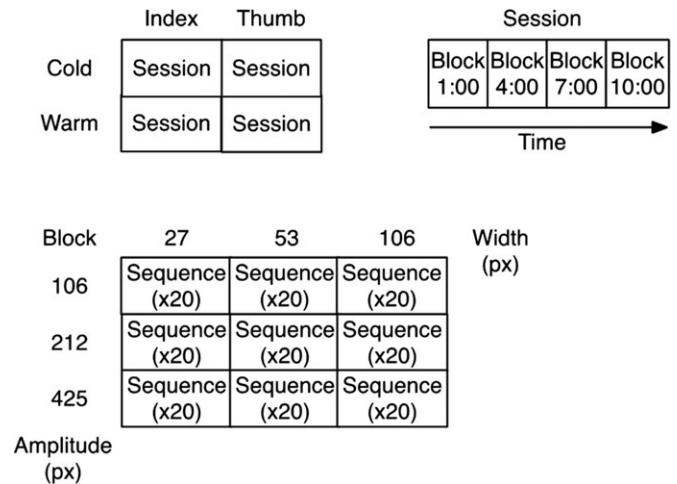


**Figure 2.** Grant squirrel meter/logger (series 1000) and a participant's hand with thermal sensors attached.

### 3.4. Procedure

Participants arrived at the warm room, where they were initially briefed on the purpose of the study. We then recorded their personal details (age, gender and index/thumb circumference) and asked them to sign a consent form if they agreed to the study specifications. We then attached the two thermistors to their thumb and index fingers while making sure the wires did not interfere with participants' movement. For training purposes, we asked participants to freely interact with our smartphone and software so they became accustomed to the setting. They then completed one full session with both of the interaction modes (one-handed and two-handed), which we discarded from our data analysis. Reception and training of participants lasted 20–30 min, and was designed to ensure that learning effects (Havenith *et al.*, 1995) and performance variations (Potter *et al.*, 1988) are minimized, and participants' finger temperature is stabilized.

After training, participants were dressed in our winter attire and shown to the cold chamber to begin the experiment. Each participant completed four experimental sessions as follows: cold–warm–cold–warm (Fig. 3), and during the whole experiment participants were standing. We decided not to counterbalance the order in which participants experience the warm and cold rooms for two reasons. First, all participants were inevitably exposed to room temperature before beginning our study, and counterbalancing would require exposing half of the participants to the cold chamber three times. Second, following ethical recommendations, we decided to minimize the time we exposed our participants to the cold chamber, keeping it to two visits for each participant. Finally, we precisely timed participants' exposure to cold by running trials at specific time periods instead of waiting until participants reached certain finger temperatures. This is because we treat finger



**Figure 3.** Experimental setup diagram.

temperature as a continuous rather than categorical variable, and wanted to have a range of finger temperature values in our analysis. The four sessions tested either the thumb (one-handed) or index finger (two-handed) for interacting with the smartphone. The order of active finger was counterbalanced, and once a session was completed the participants switched rooms and continued with the next session. Thus, the order of the four sessions was either [cold-thumb, warm-thumb, cold-index, warm-index] or [cold-index, warm-index, cold-thumb, warm-thumb].

In every session, a researcher kept strict timing using a handheld timer. Once a participant entered a room, the scientist began the timer. When the timer reached 1:00 (1 min), the participant was instructed to begin Block 1, which consisted of 180 target selection tasks of varied amplitude and width in randomized order (Fig. 1). A block typically lasted 90 s, and once a block of tasks was finished, participants waited (with their hands lowered to a natural position) for the scientist to hand them back the phone and signal to begin the next block. The blocks were timed to begin at 1:00, 4:00, 7:00 and 10:00 within a given session. Hence, our experimental design controlled the exposure time of participants to the cold and warm rooms.

### 3.5. Measures

The smartphone and thermal data collector logged data independently, and their clocks were synchronized at the beginning of each day. The following parameters were measured overall.

- (i) Movement time—time taken to complete the movement to hit the target (milliseconds).
- (ii) Offset—distance of hit from target center, used to calculate effective amplitude and width (Fitts, 1954).

- (iii) Error rate—percentage of unsuccessful target hits in a given sequence of 20 tasks (0–1).
- (iv) Throughput—the index of performance for a given sequence of 20 tasks (bits per second).
- (v) Effective index of difficulty—difficulty of a target selection task (bits).
- (vi) Index finger temperature—temperature of the index finger ( $^{\circ}\text{C}$ ).
- (vii) Thumb temperature—temperature of the thumb ( $^{\circ}\text{C}$ ).
- (viii) Active finger—which finger was used for target selection (index and thumb).
- (ix) Finger circumference—circumference of the base of the finger, measured with a finger circumference gauge (millimeters).

## 4. RESULTS

The experiment (including intake, training and experiment) lasted ~90 min per participant, and the scientists studied four participants per day. Each participant completed a total of 2280 (attempted) target hits (4 sessions  $\times$  4 blocks  $\times$  180 tasks). Overall, we collected 54 720 target hits from 24 participants, and independent thermal data from two fingers per participant every 10 s. All data were timestamped to enable *post hoc* synchronization.

### 4.1. Hardware performance

All equipment in our study has been certified for use in cold temperatures, except the smartphone. We ran a small benchmark test to determine if the handset (Samsung Galaxy S4) used in our experiment did not significantly change performance under varying ambient temperatures. We used the [AnTuTu Benchmark application \(2015\)](#) on the handset, and

conducted five complete benchmarks in both warm and cold. The results showed that the device did not substantially change its performance when ambient temperature changed ( $F(1,8) = 0.97$ ,  $P = 0.35$ ). Therefore, we used this device to ensure that ambient temperature does not inadvertently affect the recorded data.

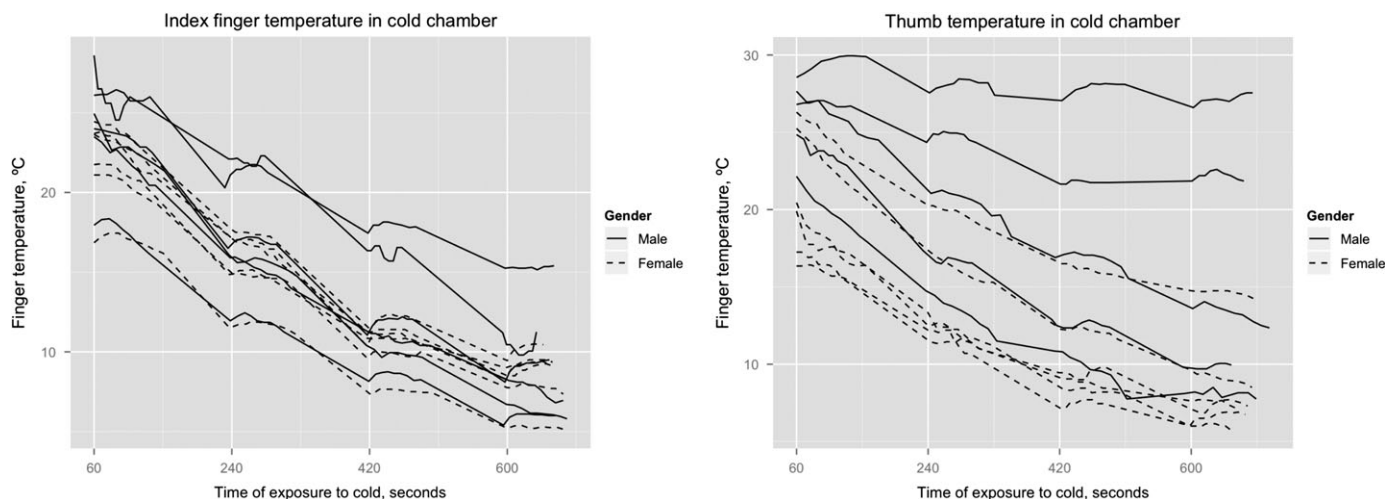
### 4.2. Physiological response

We visualize participants' physiological response by calculating their finger temperature during their first 10-min exposure to the cold chamber, and their subsequent exposure to the warm room (Figs 4 and 5). The data are grouped by gender and finger (thumb and index).

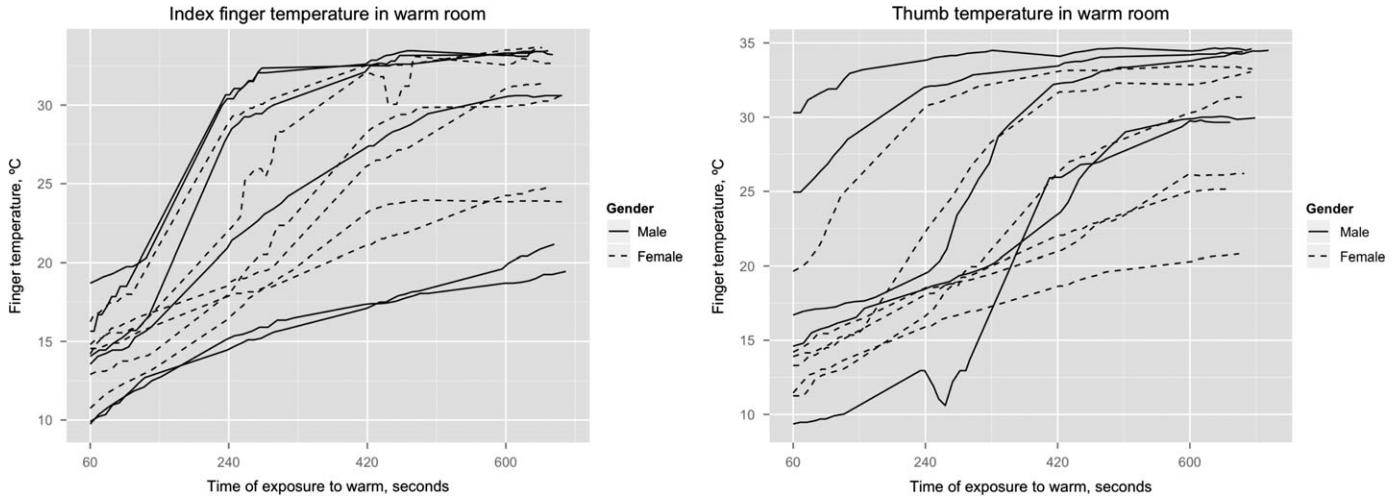
Each participant exhibits finger temperature spikes, which coincide with the timing of their task blocks. This suggests that participants' fingers were slightly warming up while performing the tapping tasks. The graphs also show that in general female participants had lower finger temperature and higher cooling rates than male participants. These observations, however, do not affect our results as the analysis was conducted based on finger temperature. A regression on the effect of finger circumference on cooling rate for both fingers was not significant for index finger and thumb, respectively ( $R^2 = 0.01$ ,  $P = 0.75$  and  $R^2 = 0.04$ ,  $P = 0.41$ ). We did not analyze differences between gender as finger circumferences is a more reliable measure ([Morton and Provins, 1960](#)).

### 4.3. Task performance

[Mackenzie's \(2015\)](#) software calculates for each 20-task sequence: throughput (using Welford's method (1968)), error rate, movement time, effective index of difficulty, effective amplitude and effective width. We refer to [Mackenzie's \(2015\)](#)



**Figure 4.** Indicative finger temperature drop when entering the cold chamber for the first time.



**Figure 5.** Indicative finger temperature rise when entering the warm room for the first time.

for details on implementation of said parameters. Data from one participant (P06) were removed because he made 100% error on the majority of their task sequences (90 task sequences).

We developed a method to analyze this data as a whole, and quantify the effect of finger temperature on performance. This is not straightforward, because we treat finger temperature as a continuous variable (rather than categorical) and therefore use regression modeling rather than Analysis of Variance test. However, due to varying physiological responses, the distribution of finger temperature is skewed toward higher temperatures, leading to relatively less data points at lower finger temperatures. For this reason, we decided to bin the finger temperature variable into five-degree bins (we also considered four- and three-degree bins with similar results, but five-degree interval was ultimately chosen following the application of the Freedman–Diaconis rule, which is a robust method that optimizes the number of bins in a histogram). Then, average values of throughput were calculated per 5°C interval.

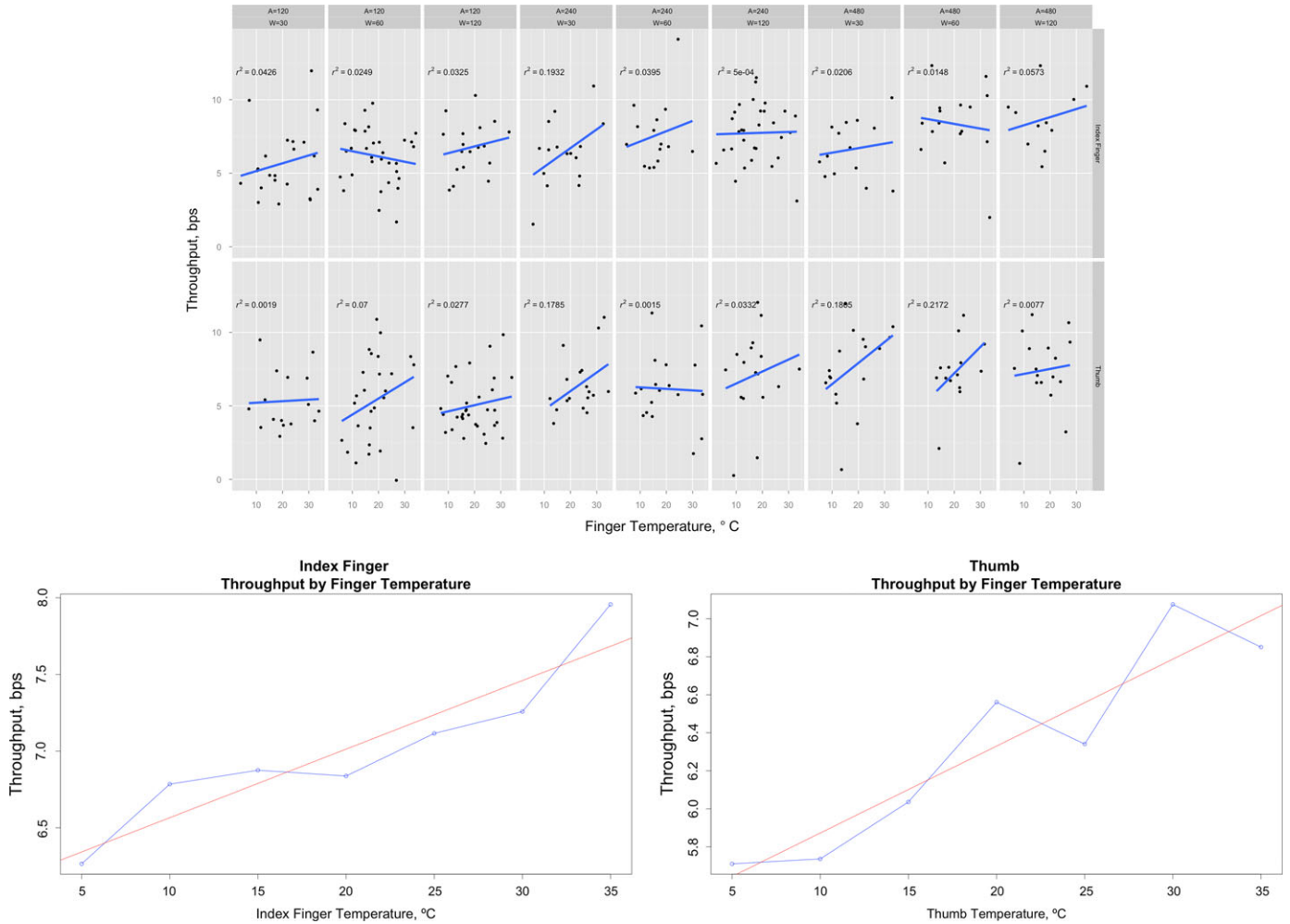
Since binning and averaging obscure the underlying data, we also show the raw underlying data in our analysis. Average finger temperature values were calculated per individual sequence, and regression analysis was performed for finger temperature and throughput. In the top of Fig. 6, we show the underlying trends in the raw data by visualizing all combinations of amplitude, width and finger (index and thumb). Then, in the bottom of Fig. 6, we show our analyses of the binned data. Using this binned data, we perform a linear regression of finger temperature on throughput, which showed a strong fit for both index finger ( $R^2 = 0.87$ ,  $F(1,5) = 31.53$ ,  $P < 0.01$ ) and thumb ( $R^2 = 0.86$ ,  $F(1,5) = 30.70$ ,  $P < 0.01$ ). These results indicate that higher finger temperature was associated with higher throughput for both fingers. This is corroborated by the analysis of the underlying raw data (Fig. 6 top): we observe that for both fingers,

most of the trend lines are positive, two negative trend lines for the index finger and only one negative trend line for the thumb. Note that we refer to the active finger, i.e. the finger (index/thumb) used for target selection in each block.

An identical procedure was followed to analyze the relationship between finger temperature and error rate: the underlying trends of the data are shown in the top of Fig. 7, while the analysis of the binned data is shown in the bottom of Fig. 7. A linear regression of error rate and finger temperature on the binned data showed no fit for index finger ( $R^2 = 0.07$ ,  $F(1,5) = 0.40$ ,  $P = 0.55$ ), but was significant for thumb ( $R^2 = 0.73$ ,  $F(1,5) = 13.19$ ,  $P = 0.02$ ). The results suggest that higher finger temperature led to reduced error rates for the thumb, but not for the index finger. Again, these results coincide with the raw data analysis (Fig. 7 top) where we observe that almost all trendlines are negative for the thumb, while for the index finger some are strongly positive.

#### 4.4. Adaptation of Fitts' law formula

Our results above show a positive relationship between finger temperature and throughput. The latter measure is calculated as: effective index of difficulty/movement time. Therefore, our results suggest that a positive correlation should also be expected between finger temperature and effective index of difficulty. Following the same analysis approach as previously (underlying data in Fig. 8 top; binned data in Fig. 8 bottom), a regression of finger temperature on effective index of difficulty was significant for both index finger ( $R^2 = 0.59$ ,  $F(1,5) = 7.15$ ,  $P = 0.04$ ) and thumb ( $R^2 = 0.98$ ,  $F(1,5) = 302.90$ ,  $P < 0.01$ ), suggesting that higher finger temperature leads to higher effective index of difficulty. Note that the definition of effective index of difficulty is  $\log_2(A_e/W_e + 1)$ , and therefore our results suggest that higher



**Figure 6.** Top: throughput for each amplitude and width combination by finger temperature. Bottom: overall throughput by finger temperature.

finger temperature is associated with smaller effective width ( $W_e$ ), i.e. with more accurate performance.

We further investigate if finger temperature can be used to predict movement time. A regression of the Standard Model that uses [Welford's \(1968\)](#) formulation  $MT = a + b \times ID_e$  (where  $ID_e$  is effective index of difficulty) showed a fit of  $R^2 = 0.27$  ( $F(1,170) = 61.40$ ,  $P < 0.01$ ) for index finger and  $R^2 = 0.11$  ( $F(1,174) = 21.38$ ,  $P < 0.01$ ) for thumb. A regression of our Extended Model using the formulation  $MT = a + b \times ID_e + c \times \text{Temperature}$  showed an improved fit for index finger ( $R^2 = 0.30$ ,  $F(2,169) = 36.35$ ,  $P < 0.01$ ) and for thumb ( $R^2 = 0.12$ ,  $F(2,173) = 11.48$ ,  $P < 0.01$ ). Both models are shown in [Figs 9 and 10](#) for index finger and thumb, respectively. The coefficients for the extended model are shown in [Table 1](#).

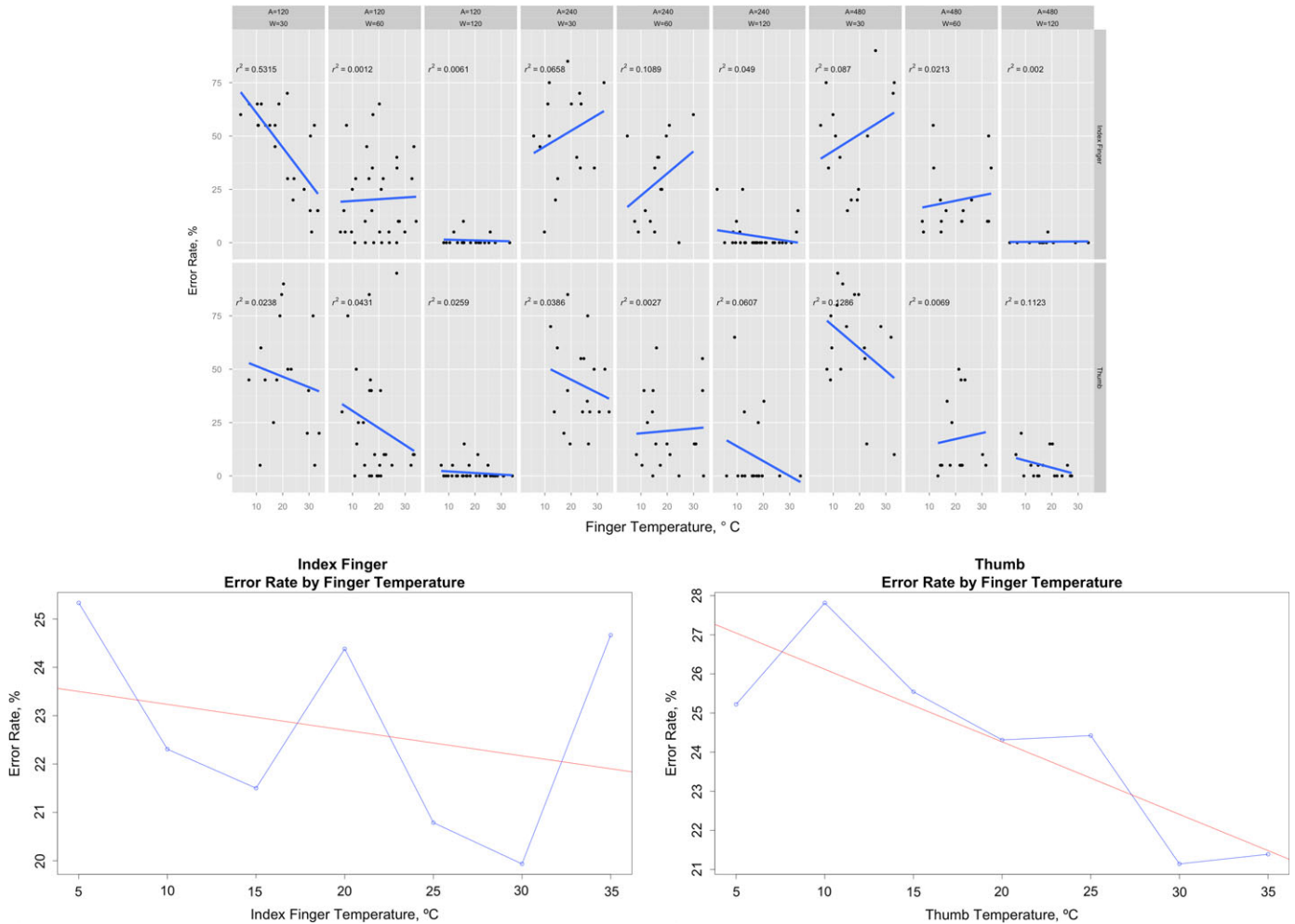
We note that we also attempted to extend the standard model by reformulating the definition of  $ID_e$  ( $ID_e = \log_2(A_e/W_e + 1)$ ). For instance, we reformulated the definition as  $ID_{e1} = \log_2(A_e/W_e + 1 \times \text{Temperature})$  and  $ID_{e2} = \log_2(A_e \times \text{Temperature}/W_e + 1)$ , but the resulting

model had a poor fit with movement time for both the former (index  $R^2 = 0.05$ ,  $P = 0.03$ ; thumb  $R^2 = 0.02$ ,  $P < 0.08$ ), and the latter (index  $R^2 < 0.01$ ,  $P = 0.65$ ; thumb  $R^2 < 0.01$ ,  $P = 0.49$ ).

## 5. DISCUSSION

### 5.1. Tapping tasks on mobile device in cold climates

This study examined the effect of finger temperature on user performance in completing tapping tasks in the context of a Fitts' law study. In our study, we found that finger temperature significantly affected user performance in both one-handed and two-handed operations. Particularly, in one-handed mode (i.e. using the thumb), users with warmer fingers had higher throughput and lower error rates. However, in two-handed mode (i.e. using the index finger), higher finger temperatures were associated with higher throughput, but did not matter for the error rate. These findings are partially corroborated by previous research that



**Figure 7.** Top: error rate for each amplitude and width combination by finger temperature. Bottom: overall error rate by finger temperature.

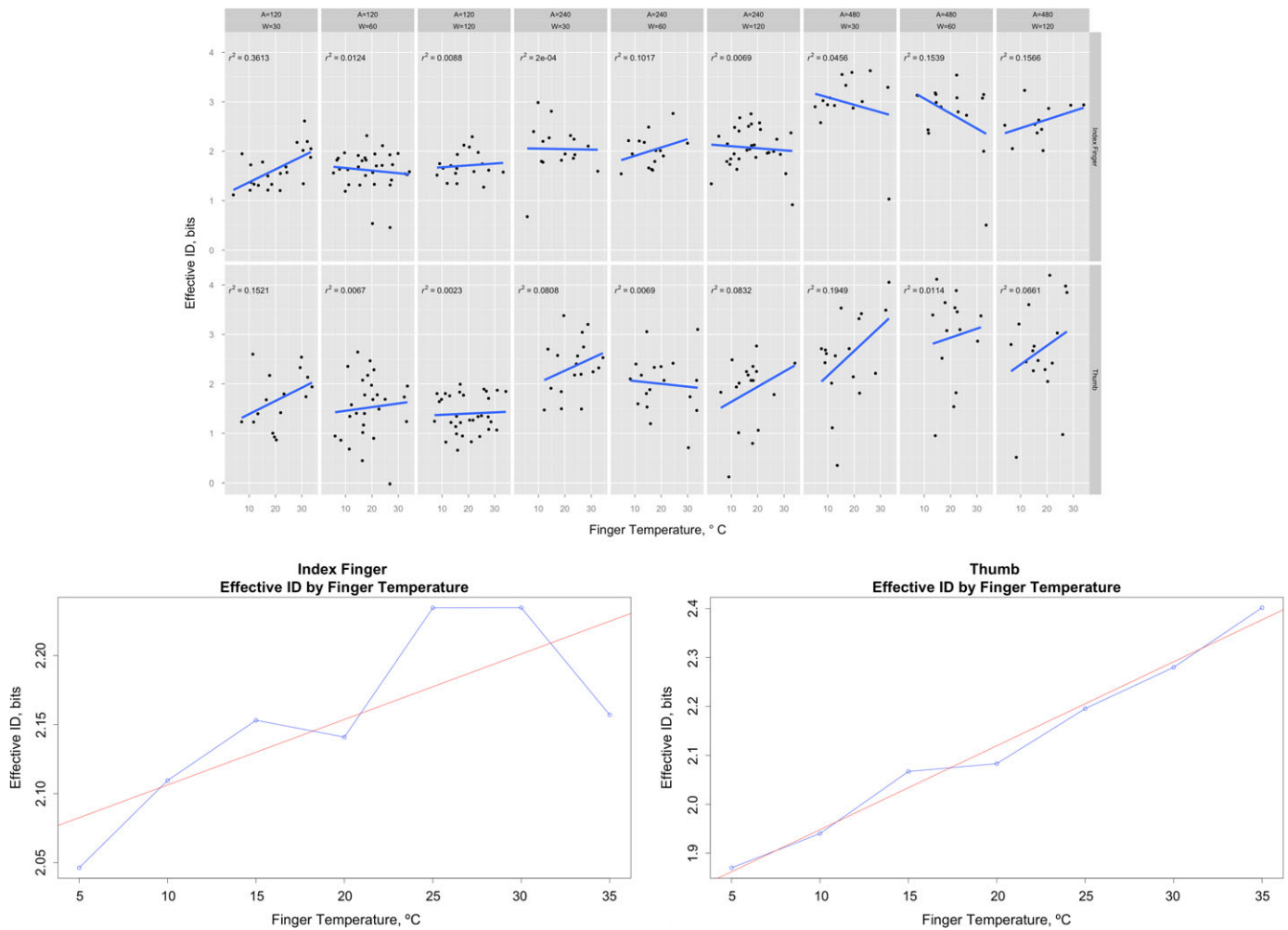
reports an effect of cold fingers on movement time, but did not establish effect of cold hands on error rate (Blomkvist and Gard, 2000). One potential reason why this effect was stronger in one-handed operation (i.e. using the thumb) is that for completing the tapping task, it required thumb movement and dexterity, whereas when completing the task with the index finger, no finger dexterity was required since the task required more of the wrist movement, than finger movement. In other words, the increased motor difficulty in completing the tasks using the thumb may have increased the effect of finger temperature on input performance due to its required dexterity, a factor that is affected by the finger temperature.

Furthermore, for both modes, there was an effect of finger temperature on effective index of difficulty meaning that users with warmer fingers are able to complete complex tasks more accurately. This is of particular importance, since in our experiment we used a simple tapping task to examine how people's behavior differs in cold temperatures. Even though this task did not require high finger dexterity, there was a

high and significant correlation between user input performance when completing tapping tasks and finger temperature for one-handed interaction, meaning that cold can affect how people use smartphones even for simple tasks. In everyday life, we expect people to use mobile devices for more difficult tasks. Hence, when completing more complex tasks, such as writing a text or an email message, under similar circumstances would result in even higher error rates and a greater performance loss due to increased dexterity demands (Yeshnik, 1988; Havenith *et al.*, 1995).

Finally, we also attempted to extend Fitts' law formula for movement time. The model we propose includes finger temperature as a parameter and gives ~11% and 9% relative improvement for the index finger and the thumb, respectively (3/27 for index and 1/11 for thumb) in comparison with the original model. The significance of this improvement implies that the finger temperature parameter is important for movement time calculation and should be accounted in Fitts' law formula.



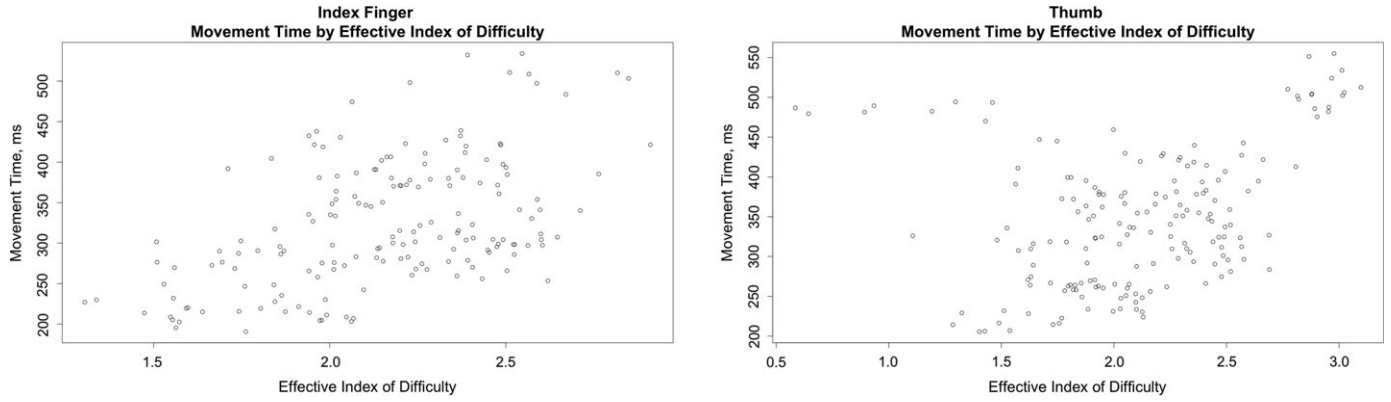


**Figure 8.** Top: effective index of difficulty for each amplitude and width combination by finger temperature. Bottom: overall effective index of difficulty by finger temperature.

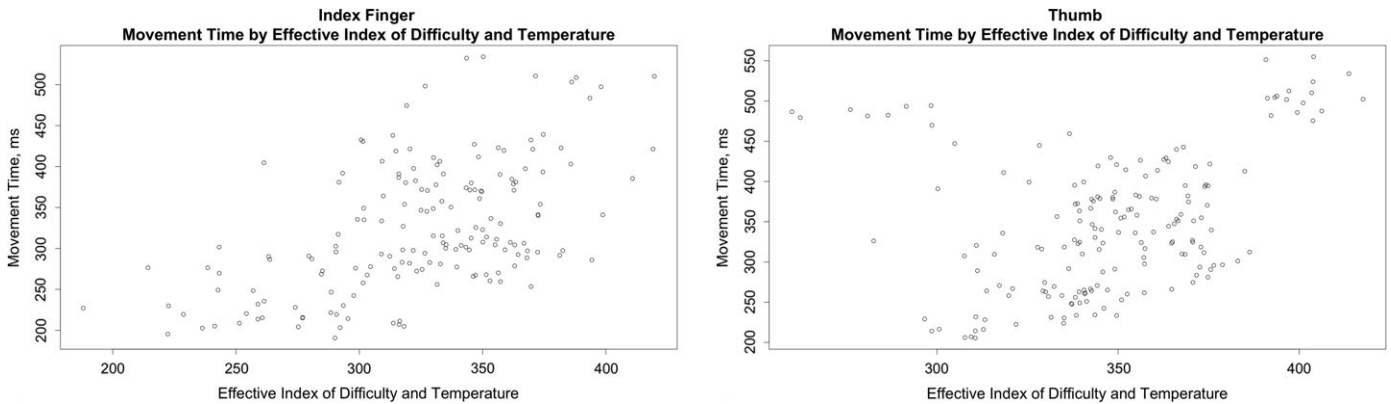
## 5.2. Adapting mobile interfaces to cold climates

Our findings imply that user performance when using mobile devices depends on user's finger temperature, hence it should be considered as a factor for interface adjustments on mobile devices. Unfortunately, cold research is relatively underdeveloped within the human-computer interaction (HCI) community (Halvey *et al.*, 2012; Polacek *et al.*, 2013; Ylipulli *et al.*, 2014). Previous work on the effect of cold fingers on technology use and our own results indicate that technology interfaces should adapt when considering colder climates. Our findings can be applied to a number of different public interfaces that are used in cold environments, such as public displays (Hosio *et al.*, 2013; Ylipulli *et al.*, 2014; Hosio *et al.*, 2014a; Hosio *et al.*, 2014b) as well as personal devices that can be used on the go (Goncalves *et al.*, 2014b), such as tablets and mobile phones. For instance, this could be achieved on mobile phones by increasing the size of buttons or employing accuracy-improving input techniques such as

Fat Thumb by Boring *et al.* (2012) or GraspZoom by Miyaki and Rekimoto (2009). In more extreme cases, notifying the user of possible risk of frostbite is a viable future use case. It is important to understand that changes to the interface may be applied in real time and can rely on both contextual information and user behavioral performance. Using only contextual information from the mobile phone's sensors might be ambiguous, because while using mobile device, the user might be warming up his hands by putting them in the pocket or breathing on them. However, contextual cues are important for indicating events (Goncalves *et al.*, 2013), such as detecting ambient temperature, time of exposure to cold and location. Also, people lose heat at different rates, as can be seen from Figs 4 and 5 and their performance varies; therefore, it is important to consider personal behavioral patterns in adaptation. For instance, previous research has shown that cultural and anthropometric factors need to be taken into consideration when designing mobile interfaces (Katre 2010).



**Figure 9.** Left: the standard model for predicting movement time ( $MT = a + b \times ID_e$ ) for index finger. Right: the standard model for predicting movement time ( $MT = a + b \times ID_e$ ) for thumb.



**Figure 10.** Left: our extended model ( $MT = a + b \times ID_e + c \times \text{Temperature}$ ) for index finger. Right: our extended model ( $MT = a + b \times ID_e + c \times \text{Temperature}$ ) for thumb.

**Table 1.** Coefficients for multiple regression model.

	Estimate	Std. err.	<i>t</i> -Value	<i>p</i> -Value
Index finger				
Intercept	82.70	34.75	2.38	0.02
$ID_e$	128.83	15.55	8.27	<0.01
Temperature	-1.89	0.65	-2.93	<0.01
Thumb				
Intercept	231.22	29.68	7.79	<0.01
$ID_e$	65.19	13.60	4.79	<0.01
Temperature	-1.05	0.85	-1.23	0.22

When loss in input performance when completing tapping tasks is detected, it can be useful to adapt the mobile interface. The loss of manual dexterity in the cold can be considered to resemble behavior of motor-impaired users, and therefore some past design implications for smartphones can be revisited. Several design implications have been recommended to make touch-based devices more accessible for people with motor impairments (Trewin *et al.*, 2013;

Nicolau *et al.*, 2014; Zhong *et al.*, 2015). For example, Nicolau *et al.* (2014) recommend to have tapping as the main interaction method meaning that swipe gestures should be scarcely or not at all used. Guerreiro *et al.* (2010) have found that people with motor impairments find it is easier to select targets at the bottom of the screen. Therefore, target position could favor the bottom of the screen when finger temperature reaches a certain threshold, particularly when considering one-handed interaction. Previous work has also advised to filter unintentional touch gestures (Anthony *et al.*, 2013; Trewin *et al.*, 2013; Naftali and Findlater, 2014) and enhance the touch area (Zhong *et al.*, 2015). In addition, voice-to-text and voice control options of mobile devices would be favored not only by motor-impaired people (Naftali and Findlater, 2014), but also could be applicable for using mobile phone in cold temperatures. Such voice controls have also been proposed for public display use in cold temperatures to prevent users from having to remove their gloves to interact with the touchscreen (Goncalves *et al.*, 2014a). The similarities between effects of cold and motor impairment, and therefore the validity of the proposed design implications, offer a new avenue for future research.

Finally, due to individual differences in cooling rates and performance, it should be possible to design a self-training interface, which would be trained on a particular user's performance data, and, hence, recognize behavioral patterns and adapt accordingly. A similar idea for personalization was suggested by Goel *et al.* (2012) and might improve user experience due to increased classification accuracy. So, for example, if an interface was trained to detect some rate of typing errors at particular outdoor settings, it could determine that the user is suffering from cold fingers and follow some of the interface adaptations mentioned previously.

### 5.3. Limitations

This study had several limitations. First, we tested only 1D target selection. Second, we constrained the task to be completed either by involving the index finger or thumb, unlike in naturalistic settings where users involve more fingers or interchange them while accomplishing any goal on their mobile device. However, these were the requirements to control and detect differences in the performance of our participants in the two main modes of operation.

Another limitation was that we did not counterbalance the order of presenting participants to cold and warm rooms due to ethical concerns and methodological reasons, and this might have influenced our results. Furthermore, some participants might have been more acclimatized to cold climate conditions, for example were born in Nordic countries. Moreover, other factors such as gender, finger circumference and metabolic rate affected cooling-down rates. Nevertheless, the analysis was done based on finger temperature instead of these factors to enable a fair comparison regarding performance loss in cold temperature. Furthermore, our experiment was conducted in  $-10^{\circ}\text{C}$  temperature in the cold chamber meaning that our findings apply to locations with similar climate conditions, and to a lesser extent, locations with slightly warmer climate. Another limitation of our study is a possible adverse performance of mobile device in a cold ambiance. Although we tried to control this issue by running a benchmark test, we cannot guarantee that the device's performance was not affected by the cold environment.

Finally, we used a cold chamber to simulate cold climate conditions and did not run the study under the natural environmental settings. This allowed us create fair conditions for running the experiment by maintaining constant temperature and controlling climate factors such as precipitations, wind chill, wind speed and humidity. Previous work by Blomkvist and Gard (2000) used local immersion of a hand in snow-water mixture to cool participants' hands. However, this approach is flawed as the cooling was performed only locally and rather abruptly which is rarely observed in naturalistic settings.

## 6. CONCLUSION AND FUTURE WORK

Our work describes a controlled laboratory experiment on the effect of cold temperature on smartphone usage, and particularly on tapping tasks. We show that colder temperature is associated with lower throughput and higher error when using the phone in two-handed operation (but not one-handed). We also find that lower temperatures are associated with less accurate performance for both one-handed and two-handed operations. Finally, we demonstrate that the use of finger temperature can increase the predictive power of Fitts' law in estimating movement time.

Our results highlight the performance hit that users suffer when using their smartphones in cold temperatures, and a variety of design recommendations from the literature can be considered as a countermeasure. For example, new and optimized interaction techniques can be explored to automatically adapt and enhance smartphone input capabilities when in cold temperatures. Further work is needed in HCI to study task performance when using mobile and urban technologies in cold temperature, including public displays, cash machines (both touchscreen and keyboard-based), smartphones (touch-based and keyboard-based) and potentially wearable technologies (smart watches, smart glasses, skin conductivity systems and augmented reality).

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