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ASSESSMENT OF MOBILE INTERACTION PERFORMANCE IN COLD ENVIRONMENTS

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ABSTRACT

The importance of understanding the effect of situational impairments on mobile phone use cannot be overestimated. Here, we investigate one such type of situational impairment, cold temperature, on mobile interaction performance, which can open up research opportunities for improvement of mobile interfaces to cater to these environments. To this end, we present two studies aimed at 1) assessing the effect of a cold environment on smartphone input performance and target acquisition, and 2) assessing effect of cold environment on fine-motor skills and vigilance during interaction with a smartphone.

The results of the first study show that cold ambiance affects smartphone input performance. We demonstrate that colder temperatures are associated with lower throughput and higher error rate when using mobile devices in two-handed interaction mode (but not one-handed). Further, we demonstrate that the use of finger temperature can improve the predictive power of Fitts' law in estimating movement time.

The results of the second study show that the cold environment adversely affected participants' fine-motor skills performance, but not vigilance. In particular, participants' touch gestures in the cold chamber had a significantly bigger offset size than in the warm room. However, we did not observe a significant effect of cold temperatures on participants' vigilance. Based on our results, we highlight the importance of correcting measurements when investigating performance of cognitive tasks to take into account the physical element of said tasks.

Finally, we identify and discuss a number of design recommendations from literature that application designers can consider as a countermeasure to decreases in smartphone input performance in cold environments.

Keywords: Smartphones, ubiquitous computing, cold temperature, situational impairments, mobile interaction, smartphone input performance, Fitts' law, fine-motor movements, offset, vigilance, mobile interface.

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TIIVISTELMÄ

Paikallisten rajoitetekijöiden ymmärtämisen tärkeyttä mobiililaitteilla ei voi yliarvioida. Tässä työssä tutkimme yhtä rajoitetekijän, kylmän lämpötilan, vuorovaikutusta mobiililaitteden käytön suorituskyvyssä, joka voi avata uusia tutkimusmahdollisuuksia mobiilaitteiden käyttöliittymien suunnittelussa tämän kaltaisissa ympäristöissä. Tämän saavuttaaksemme, esitämme kaksi tutkimusta, joiden aiheina ovat 1) kylmän ympäristön vaikutus älypuhelimen syöttösuorituskykyyn ja kohteen löytämiseen, sekä 2) kylmän ympäristön vaikutus hienomotorisiin suorituksiin sekä valppauteen älypuhelinta käytettäessä.

Ensimmäisen tutkimuksen tulokset näyttivät, että kylmällä ilmapiirillä on vaikutus älypuhelimen syöttösuorituskykyyn. Näytämme, miten kylmemmät lämpötilat assosioivat matalampaan suoritustehoon sekä suurempaan virhemäärään, kun mobiililaitetta käytetään kahdella kädellä (mutta tulokset eivät päde yhden käden käyttöön). Lisäksi esitämme, että sormen lämpötilan käyttö muuttujana voi parantaa Fittsin lain ennustusta siirtymisajan arvioinnissa.

Toisen tutkimuksen tulokset näyttivät, että kylmä ympäristö vaikuttaa epäsuotuisasti tutkimukseen osallistujien motorisiin suorituksiin, mutta ei valppauteen. Erityisesti osallistujien kosketustarkkuus kohteisiin oli matalampi kylmähuoneessa, kuin normaalissa huonelämpötilassa. Osallistujien valppaus ei kuitenkaan kärsinyt kylmässä lämpötilassa. Näiden tulosten perusteella korostamme tehtävien muokkaamista suunnitteluvaiheessa, jossa otetaan huomioon tehtävän fyysiset elementit.

Viimeiseksi tunnistamme ja keskustelemme aiemman kirjallisuuden ehdottamista suunnittelusuosituksista, joita ohjelmistokehittävät voivat harkita vastakeinona älypuhelimien syöttösuorituskyvyn muutoksiin kylmissä ympäristöissä.

Avainsanat: älypuhelimet, jokapaikan tietotekniikka, kylmä lämpötila, paikalliset rajoitetekijät, mobiilivuorovaikutus, älypuhelimen syöttösuorituskyky, Fittsin laki, hienomotoriikka, tarkkuus, valppaus, mobiilikäyttöliittymät.

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FOREWORD

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ABBREVIATIONS

ANOVA	Analysis of Variance test
A	Fitts' Amplitude
A_e	Effective Fitts' amplitude
App	Application
ºC	degrees Celsius
HCI	Human-computer interaction
ID	Fitts' index of difficulty
ID_e	Fitts' effective index of difficulty
M	mean
min	minutes
ms	milliseconds
m/s	meters per second
MT	movement time
p	probability
px	pixels
SD	standard deviation
Tukey HSD	Tukey's honest significance difference test
W	Fitts' width
W_e	Fitts' effective width
UbiComp	Ubiquitous Computing
χ^2	Chi-squared test
κ	Cohen's kappa coefficient
R^2	coefficient of determination
%	percent

1. INTRODUCTION

The purpose of this Master's Thesis is to investigate the effect of cold environments on mobile device interaction. Particularly, we investigate the effect of a cold environment on smartphone input performance and target acquisition, and the effect of cold exposure on vigilance and fine-motor movements during interaction with a mobile device.

Despite the de-facto prominence of UbiComp experiments "beyond the desktop" and "in the wild", relatively little work has investigated how interaction itself is shaped by non-conventional environments, which can lead to situational impairments [75]. Specifically, very little work has systematically investigated how ambient temperature shapes interaction with mobile devices, even though ambient temperature substantially deviates geographically, seasonally, and diurnally. This work has significant contribution to HCI research, especially in the field of designing mobile interfaces and adapting them to situational impairments, caused by various factors, particularly cold. To the best of our knowledge, there exists no research work targeted to study physical and cognitive aspects of mobile interaction in cold environments.

A typical scenario in cold climates is for users to interact with their devices in outdoor settings. While touch screen 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 touch screen gloves [25], discomfort during extensive typing [25], and humans' tendency to misplace their stylus [48]. As a result, individuals are likely to use their smartphones with their bare hands in cold outdoor settings, possibly affecting their input performance.

Moreover, since cooling of the tissue may result in degraded physical [60] and mental [51] performance, completing the same task in cold can require extra effort compared to a warm environment [42]. Physical interaction with mobile devices may also be adversely affected in cold due to muscular dexterity loss [30] and shivering, which may in turn disturb fine motor control. Hence, a better regulation of movements may be required to perform motor-tasks compared to a warm environment [60]. Further, research shows that discomfort caused by cold can adversely affect tasks requiring concentration and vigilance [42]. It also deflects attention from primary task and results in impaired cognitive performance [65,69].

There exists a rich literature on how situational factors can impair input on mobile devices, such as motion [19,33], divided attention [32], ambient noise [75], and mood [22]. However, while it is well established that cold temperatures affect vigilance amongst other cognitive capabilities [65,69], and fine-motor movements [60], 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 [24]. Therefore, we conducted two experimental studies within the scope of this Thesis. We carried out the first experiment to investigate if ambient and finger temperature affect users' input performance on a smartphone. In particular, we measured movement time, error rate and throughput during Fitts' law tests on a smartphone. The experiment quantified users' performance in cold climates and settings, and suggested that adjusting target's effective size can improve performance and reduce errors. We also provided a reformulation of Fitts' law formula for movement time that takes into account temperature. The model we propose gives about 8% relative improvement (2/23 for

index and 3/39 for thumb) in comparison with the original model. As for the second experimental study, we investigated the effect of a cold environment on fine-motor movements and vigilance during mobile interaction. To investigate the effect of cold on fine-motor movements we measured the accuracy of touch gestures by offset size. We used reaction time and errors to measure the effect of cold on cognitive skills as recommended in [16]. For both experiments, we used two interaction modes with the device: one-handed and two-handed. One-handed interaction presumes holding the device with the dominant hand and interacting with it with the thumb of the same hand, while two-handed interaction mode presumes holding the device with the non-dominant hand and interacting with it with the index finger of the dominant hand. We describe both experiments in detail in Chapter 3.

The organisation of the Thesis is as follows. Chapter 2 provides literature review on human physiological response to cold temperatures, manual dexterity and target acquisition performance, effect of cold on fine-motor and cognitive skills, and cold as a situational impairment factor. Chapter 3 contains a detailed description of conducted experiments. Chapter 4 describes analysis and results of the studies. Chapter 5 encloses the discussion. Finally, Chapter 6 provides conclusion and limitations of the studies.

2. RELATED WORK

2.1. Situational impairments and mobile phone interaction

There is a lack of understanding of situational impairments and their impact on mobile interaction [75]. Goel *et al.* emphasise that situational impairments, such as dynamic state of the phone, might affect successful interaction with the device, because current mobile devices still lack appropriate awareness of environmental context [20]. As accessibility of technology for disabled people is an important issue of modern society [21], previous work has highlighted how situational impairments may worsen user's interaction with mobile device regardless of their abilities [31], since they can be caused by various factors, such as ambient temperature, ambient light [75], ambient noise [75] and movement [19,33]. Moreover, situational impairments might cause further accessibility issues for people with disabilities when attempting to use the device in one of the mentioned situations [31]. Also, a better understanding of situational impairments can be helpful in improving accessibility for those with more permanent physical impairments, since they both might affect users in a similar way [75]. Wobbrock argues that understanding situational impairments would increase our understanding of needs for improved accessibility and adaptive user interfaces [75].

Further, when technology is being used outdoors, weather and climate become an issue [78] and, hence, might cause situational impairments when interacting with technology. Therefore, weather conditions, particularly the effect of cold, is important to study within the scope of situational impairments in interaction with mobile devices. As suggested in [75], once situational impairments are better understood, it would be beneficial to discover if physical and situational impairments have similar effect on users. In particular, cold-induced situational impairments potentially could describe physical impairments of the user.

Since cold-induced motor impairments and temporal disabilities may have common characterisation, it is important to consider literature on the use of touchscreen technology by motor-impaired individuals. Such individuals typically find conventional gestures challenging, often causing them to refrain from using touchscreen devices altogether [80]. Duff *et al.* [11] and Guerreiro *et al.* [23] report that motor-impaired individuals make more mistakes than able-bodied individuals when hitting targets on a touchscreen. Irwin & Sesto show that users with motor impairments require dwell time for tapping tasks on touchscreens [29]. Further, Wobbrock *et al.* [76] showed that tremor and fatigue adversely affected user's ability to control their movements on PDA screens using stylus. Kane *et al.* summarise problems faced by people with motor and visual disabilities when using mobile phones such as difficult interfaces with small buttons and screens, causing difficulties while reading [32]. Therefore, design implications from this area of research can potentially be adapted for able-bodied users when suffering from cold-induced decreases in manual dexterity.

2.2. Physiological response to cold temperatures

When exposed to cold temperature, the human body experiences vasoconstriction reaction of skin arteries [37,47] in an attempt to preserve body heat by reducing heat loss [30,73]. Vasoconstriction reduces blood supply to the skin and extremities [30], leading to greater heat loss from fingers [28,35,72] and decreased touch sensitivity in the hand [54]. As a result, the dexterity of extremities diminishes, joints become stiffer, and muscles lose their strength [54]. 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% [77]. In general, finger dexterity degrades when the skin temperature drops below 15 ºC [26], while sensitivity drops rapidly below skin temperatures of 6-8 ºC [44,47].

Two additional factors have been linked to physiological response to cold. First, several studies have reported gender-related differences. Specifically, females experience accelerated decrease in hand skin temperature [3] and reach lower skin temperatures [58]. 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 [34,36]. Similarly, individuals whose daily work takes place in ice chambers have a higher mean finger temperature [64], while individuals who lack indoor heating at home experience less cold and discomfort during cold exposures than those who have indoor heating [79]. Thus, gender and acclimatisation need to be controlled in studies investigating physiological response to cold.

2.3. Manual dexterity and target acquisition performance in cold

We hypothesise that cold hands and fingers can severely affect smartphone usage due to decreased manual dexterity. For instance, standardised Pegboard tests show that decreased manual dexterity significantly increases reaction time (i.e. target acquisition time) in manual tasks [30]. 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 [5] used a target size in a Fitts' acquisition task [15] 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, 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 ºC. 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, use of mouse and pen-on-tablet was not as affected by cold hands. 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 as also shown by Gentile [17].

There is a rich ergonomics literature on the effect of cold temperature. Teichner & Kobrick [66] 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 [47]. 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.

Since cold-induced motor impairment is akin to a temporary disability, it is also helpful to consider literature on the use of technology by motor-impaired individuals, particularly touchscreens. Such individuals typically find conventional gestures challenging, often causing them to refrain from using touchscreen devices altogether [80]. Duff *et al.* [11] and Guerreiro *et al.* [23] report that motor-impaired individuals make more mistakes than able-bodied individuals when hitting targets on a touchscreen. Irwin & Sesto show that users with motor impairments require dwell time for tapping tasks on touchscreens [29]. Therefore, design implications from this area of research can potentially be adapted for able-bodied users when suffering from cold-induced decreases in manual dexterity.

This work reports the first to consider finger temperature as an input parameter for mobile devices. Our study examines the effect of cooling fingers on users' performance in completing pointing tasks in the context of a Fitts' law study. Our goal is to quantify the effect of temperature on performance and error. Unlike previous work, we do not cool fingers locally via cold water immersion, but we place our participants in cold chamber that more accurately emulates exposure to outdoor winter conditions.

2.4. Effect of cold on fine-motor performance and cognitive skills

There are two primary sets of human functions that govern how people interact with mobile devices: physical and cognitive. Physical aspects concern motor actions such as touching, pointing, and swiping. Cognitive aspects concern tasks such as finding and launching necessary applications, finding and activating commands, and responding to output, and formulating language [59]. This work focuses on how these two sets of functions are affected by a cold environment, by considering performance in terms of fine-motor movements and vigilance respectively.

Previous research has highlighted that cold exposure can severely affect fine-motor skills [9,52]. Tasks involving manipulations of fingers are more adversely affected in cold than those involving hand and arm manipulations [70,77]. For instance, standardised Pegboard tests show that decreased manual dexterity significantly increases reaction time (i.e. target acquisition time) and lowers accuracy in manual tasks [30].

Further, Havenith *et al.* demonstrate that finger dexterity decreases sharply when the skin temperature drops below 15 ºC [26]. Moreover, the more finger dexterity the task requires, the bigger the performance loss will be. Even though this effect is well documented, very little prior work has directly studied the effects of cold temperature on users' interaction with technology. As one example, Blomkvist [5] used a target size in a Fitts' acquisition task [15] 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, 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 ºC. The study reported that participants with cold hands performed slower when using trackballs which require higher finger dexterity, regardless the target size.

Regarding cognitive performance, previous work has shown that cold can have a significant impact due to the distracting power of a more stressful environment than usual [65,71]. For example, Daanen *et al.* found a deteriorating effect of cold on driving performance, and reported a 16% decrease in driving performance at temperatures of 5 ºC compared to driving performance at 20 ºC [10]. Vaughan and Strauss also documented considerable degradation in cognitive performance after exposure to cold water (4.5 ºC) compared to exposure to warmer water (15.5 ºC). Accuracy for solving simple arithmetic tasks and navigation problems fell by 11% and 9% respectively. Vigilance performance decreased by 3% in target detection task alongside with detection time, which increased by 26% [71].

Pilcher *et al.* reported that below 10 ºC cognitive skills such as reasoning, learning and memory are impaired [55]. Flouris *et al.* observe significant vigilance deterioration in a target hitting task in ambient temperatures of -20 ºC within 45 minutes of exposure to cold [16]. They also report more deteriorated vigilance in women in comparison to men. Hence, gender needs to be controlled in studies investigating physiological response to cold. Reaction time to complete a task is considered to be one of the indicators that measure vigilance [16]. Several studies report longer response times when cognitive tasks are performed while participants are exposed to cold air or water [9,62]. Furthermore, exposure to a cold room at -5 ºC increased error rate in 8-choice reaction time tasks [13,14].

We hypothesise that cold temperatures can severely affect smartphone usage due to decreased manual dexterity [60] and vigilance [71]. Particularly, we hypothesise that from a fine-motor performance perspective that offset and reaction time of touch will be larger in cold than in warm. From a cognitive skills perspective, we hypothesise that due to the adverse effect of cold on vigilance, users will take longer time and make more mistakes when asked to remember and find an icon, a common task in mobile phone use.

3. COLD CHAMBER EXPERIMENTAL STUDIES

As the purpose of this work was to investigate the effect of cold on several aspects of human performance in mobile interaction, we ran two independent studies. The first study was designed to investigate the effect of ambient and finger temperature on smartphone input performance, in particular target acquisition. Smartphone input performance was quantified with Fitts' Law Throughput, Error rate, Movement time, and Index of difficulty. This study was also designed to provide an improvement of the Fitts' Law formula by introducing a new parameter - finger temperature. The second study was mostly focusing on the effect of cold ambient temperatures on general fine-motor and cognitive skills performance, in particular accuracy of touch gesture and vigilance. The second study contained typical tasks when interacting with a mobile device, which covered both the physical aspect of interaction, such as precise tapping a target, as well as cognitive aspect of interaction, such as finding an icon amongst other icons. Touch gestures were quantified using offset size and reaction time, while cognitive skills were quantified using reaction time and errors.

3.1. Study 1: Target acquisition on smartphones in a cold environment

3.1.1. Variables

The study followed a within-subjects experimental design. The first independent variable was ambient temperature, which 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 acquisition: index finger or thumb. This also directly affects holding posture, since thumb is used in one-handed operation while index finger requires two-handed operation. Additional independent variables were introduced by the software used to conduct a one-dimensional Fitts' law test: target amplitude (120, 240, 480 pixels, specifying centre-to-centre distance between targets), and target width (30, 60, 120 pixels, specifying the width of targets). These two values were scaled by the software such that the widest condition (largest amplitude & width) spans the device's display with minus 10 pixels on each side [41]. The experimental design was approved by the Human Sciences ethics committee of our university.

3.1.2. Participants and apparatus

Participants were recruited through mailing lists. Twenty-four participants enrolled (12 male, 12 female) aged 20 to 35 years (M=26.2, SD=3.6). Gender was balanced since literature suggests that it affects physiological response to cold [3,58]. We controlled for acclimatisation to cold temperature by ensuring that all participants had lived in cold climates (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 and top garment on the day of the study. During the experiment, every participant was asked to wear an additional winter attire provided by us, consisting of a winter jacket and hat

(Figure 1). The participants were asked to not wear gloves nor warm their hands through movement, rubbing, or the pockets. Each participant was paid 40 Euros for participating.

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

Participants used a Samsung Galaxy S4 smartphone running Google's Android 4.1 (Jelly Bean) operating system with a 4-inch screen sized 540 by 960 pixels. The FittsTouch Android application by MacKenzie [41] was used to evaluate touch-based target selection using Fitts' law (Figure 1). The application was modified to disable the repetition of outlier sequences. This was required to ensure that all participants are exposed to cold for equal time periods, thus avoiding excessive cooling and minimising possible learning effects.

The experiment took place in two adjacent rooms. The warm room had a controlled ambient temperature of 24 ºC, wind velocity below 0.1 m/s, and humidity of 30-35%. The cold chamber (Figure 2 had a controlled ambient temperature of -10 ºC, wind velocity below 0.1 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 was logged every 10 seconds using a mobile battery-powered Grant Squirrel meter/logger series 1000 (Figure 3).

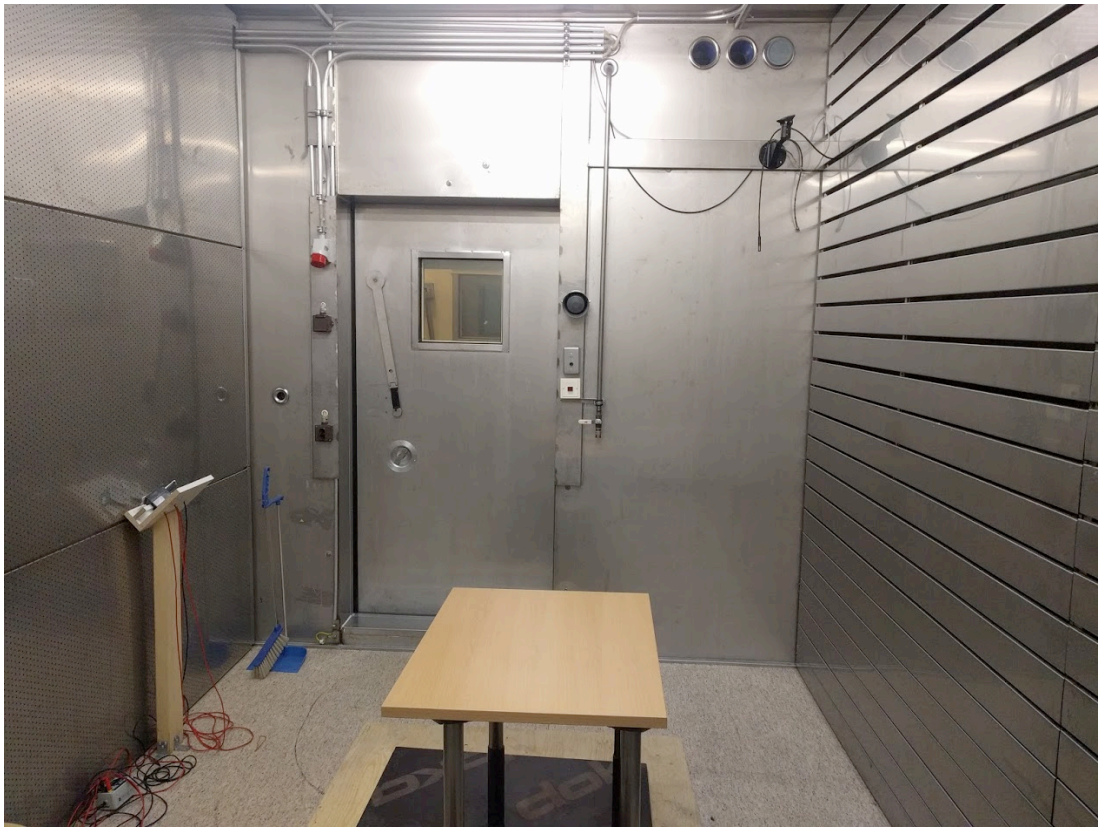

Figure 2. Cold chamber

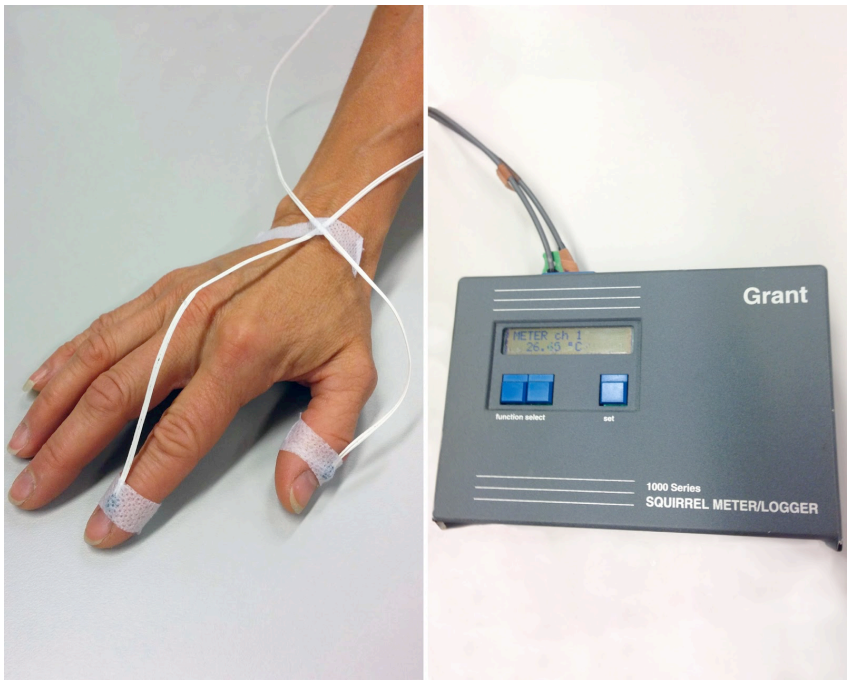

Figure 3. Grant Squirrel meter/logger (series 1000) and participant's hand with thermal sensors attached

3.1.3. Design and procedure

Participants arrived to the warm room, where they were initially briefed on the purpose of the study. We then recorded their personal details (age, gender, index/thumb circumference) and asked them to sign a consent form if they agreed to 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 we asked participants to freely interact with our smartphone and software so they become accustomed to the setting, and subsequently to complete one full session which we discarded from our data analysis. Reception and training of participants lasted 20-30 minutes, and was designed to ensure that learning effects [26] and performance variations [57] are minimised, and participants' finger temperature is stabilised.

After training, participants were dressed in our winter attire and entered the cold chamber to begin the experiment. Each participant completed 4 experimental sessions as follows: cold-warm-cold-warm (Figure 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 since they were all exposed to room temperature before beginning our study, and counterbalancing would require exposing half of the participants 3 times to the cold chamber. The 4 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 4 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, the participant was instructed to begin Block 1, which consisted of 180 target acquisition tasks of varied amplitude and width (Figure 4). A block typically lasted 90 seconds, 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, 10:00 within a given session. Our experimental design controlled the exposure time of participants to the cold and warm rooms.

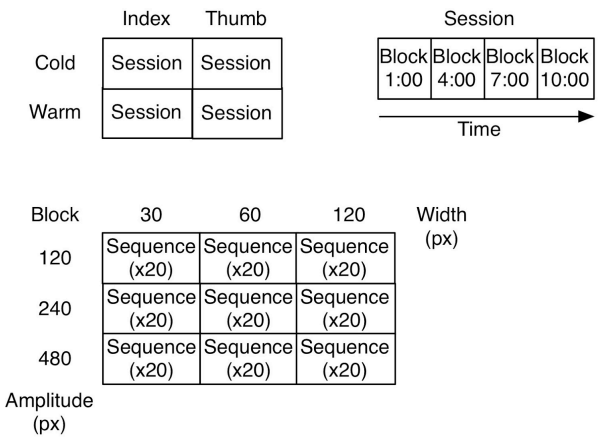

Figure 4. Experimental setup diagram

3.1.4. Measures

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

1. Movement time - time taken to complete the movement to hit the target (milliseconds).
2. Offset - distance of hit from target centre, used to calculate effective amplitude & width [15].
3. Error rate - percentage of unsuccessful target hits in a given sequence of 20 tasks (0~1).
4. Throughput - the index of performance for a given sequence of 20 tasks (bits per second).
5. Index finger temperature - temperature of the index finger (degrees Celsius)
6. Thumb temperature - temperature of the thumb (degrees Celsius).
7. Active finger - which finger was used for target acquisition (index, thumb).
8. Finger circumference - circumference of the base of the finger, measured with a finger circumference gauge (millimetres).

3.2. Study 2: Fine-motor and cognitive impairments during mobile interaction in cold environments

3.2.1. Software

Two custom Android applications called TapCircle and FindIcon were developed for this study. The TapCircle application was designed to quantify participants' fine-motor performance in a target acquisition task, while the FindIcon application was used to quantify participants' vigilance in a search task.

The TapCircle application displayed circular targets of 135 pixels radius, randomly appearing on a 4x6 grid [27], one at a time. For convenience, grid positions are numbered as shown in Figure 5. Every target had an indicated centre and participants were instructed to tap the centre of the target as precisely and as quickly as possible. We ensured that targets appeared in each of the 24 grid positions at least once in order to have data points on every grid position. Figure 6 shows the interface used by the researchers to set the conditions, and the application used by the participants. This application logged the position of the grid where a target was drawn, coordinates of the target's centre and participant's touch, and elapsed time. Only taps inside the circle were subsequently retained during data analysis.

0	1	2	3
4	5	6	7
8	9	10	11
12	13	14	15
16	17	18	19
20	21	22	23

Figure 5. Grid with 24 positions

In the FindIcon application, participants had to locate and click on a particular target icon amongst a set of 24 icons in a 4x6 grid that emulated a typical home screen of a mobile phone. The target icon was first shown to participants before each trial, and participants could look at the target icon for as long as necessary until they memorised it. The application was designed so that in each condition each of the 24 icons would be designated as the target in a random order, and that every grid position would host a target icon in a random order. This randomisation minimised any possible learning effects.

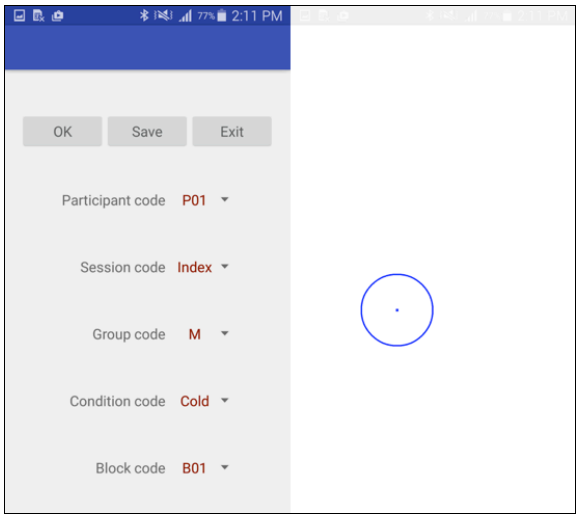

Figure 6. Interface of TapCircle application

The set of 24 icons was chosen from the list of most downloaded applications with more than 100 million downloads each [38]. Figure 7 shows the interface used by the researchers to set the conditions, and the interface of the application seen and used by the participants. We recorded the time spent on memorising the target icon, the time taken to locate and click the target icon, the grid position where the target icon was shown (including X and Y coordinates of the start and centre points of the icon), and the coordinates and timestamp of all touches made by participants. The application required participants to click on the correct icon before proceeding to the next trial, and recorded the number of wrong attempts before the correct icon was clicked. Participants performed tasks on both our applications, counterbalancing the order.

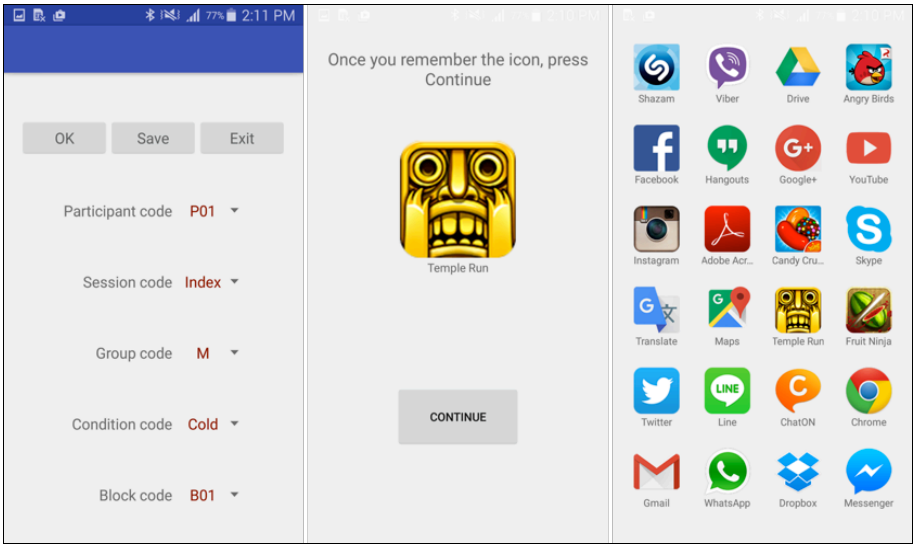

Figure 7. Interface of FindIcon application

3.2.2. Participants and apparatus

Participants were recruited through mailing lists and snowball recruitment. Twenty-four participants aged 18 to 35 years (M=24.64, SD=4.55) enrolled (12 male, 12 female). Gender was balanced since literature suggests that it affects physiological response to cold [3,16,58]. We controlled for acclimatisation to cold temperature by ensuring that all participants had lived in cold climates (e.g., Scandinavia) for more than six months. 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 (Figure 8). The participants were asked to not wear gloves nor warm their hands through movement, rubbing, or the pockets. Each participant was paid 40 Euros for participating.

Figure 8. Cold chamber setup for study 2.

Participants used a Samsung Galaxy S5 smartphone running Google's Android 5.0 (Lollipop) operating system with a 5.1-inch screen sized 1080 by 1920 pixels. The experiment took place in two adjacent chambers hosted at an arctic medical facility. The warm room had a controlled ambient temperature of 20 ºC, wind velocity below 0.1 m/s, and humidity of 30-35%. The cold chamber had a controlled ambient temperature of -10 ºC, wind velocity below 0.1 m/s, and humidity of 70-75%. Finger temperature was measured using two thermistors (Model 427, YSI Inc. USA) attached to the index finger and thumb of each participant's dominant hand, just below the nail. Thermal data was logged every 10 seconds using a mobile battery-powered Grant Squirrel meter/logger series 1000 (Figure 2). We collected this information to verify the temperature drop in the cold chamber as well as temperature rise in the warm room.

3.2.3. Design and procedure

The study followed a within-subjects experimental design. The first independent variable was the experimental setting: warm room or cold room. The second independent variable was the finger used for target acquisition: index finger or thumb. This variable was coupled with holding posture, since thumb was used in one-handed operation while index finger requires two-handed operation. The experimental design was approved by the Human Sciences ethics committee of our university.

Participants arrived to the warm room, where they were initially briefed on the purpose of the study. We then recorded their personal details (age, gender, index/thumb circumference, dominant hand) and asked them to sign a consent form if they agreed to study specifications. We then attached the two thermistors to their dominant thumb and index fingers while making sure the wires did not interfere with participants' movement. For training we asked participants to freely interact with our

smartphone and both applications so they become accustomed to the setting, and subsequently to complete 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 minutes, and was designed to ensure that learning effects [26] and performance variations [57] are minimised, and participants' finger temperature is stabilised.

After training, participants were dressed in our winter attire and shown to the cold chamber to begin the experiment. Each participant completed 4 experimental sessions as follows: cold-warm-cold-warm (Figure 9), 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 3 times. Second, following ethical recommendations we decided to minimize the time we expose our participants to the cold chamber, keeping it to 2 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 temperature as a continuous rather than categorical variable, and wanted to have a range of finger temperature values in our analysis.

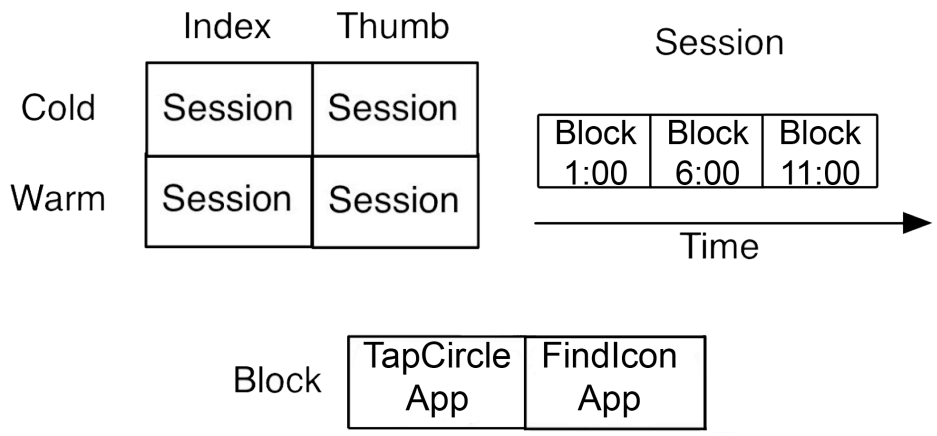

Figure 9. Experimental setup diagram

The 4 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 4 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 minute), the participant was instructed to begin Block 1 in which both applications' task was completed. The order in which applications appeared was counterbalanced between participants. A block typically lasted around 2.5 minutes in TapCircle application and 1.5 minutes in FindIcon application, and once a block of tasks was finished for both applications, 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, 6:00, 11:00 within a given session. Hence, our experimental design controlled the exposure time of participants to the cold and warm rooms.

Once the experiment was completed, participants took part in a short interview session. Regarding both applications, we enquired participants about their subjective opinion if they were more precise and/or quick when completing the tasks in any of the conditions. We then asked them to identify parts of the screen that were in their opinion harder/easier to reach (in both applications) and find the icon (application FindIcon). We also asked participants to report which of the apps used in our experiment were also installed on their phones in order to determine if this affected time taken to find an icon. Finally, we enquired what strategy they used to find an icon, and whether shape, text or colour of the icons mattered.

4. ANALYSIS AND RESULTS

4.1. Study 1: Target acquisition on smartphones in a cold environment

The experiment (including intake, training, and experiment) lasted about 90 minutes per participant, and the scientists studied 4 participants per day. Each participant completed a total of 2280 (attempted) target hits (4 sessions x 4 blocks x 180 tasks). Overall we collected 54720 target hits from 24 participants, and independent thermal data from 2 fingers per participant every 10 seconds. All data was timestamped to enable post-hoc synchronisation.

4.1.1. Physiological response

We visualise participants' physiological response by calculating their finger temperature during their first 10-minute exposure to the cold chamber, and their subsequent exposure to the warm room (Figure 10 and Figure 11). The data is grouped by gender and finger (thumb, index). Each participant exhibits spikes in Figures 4 and 5, 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 $R^2 < 0.04$, $p = 0.41$).*

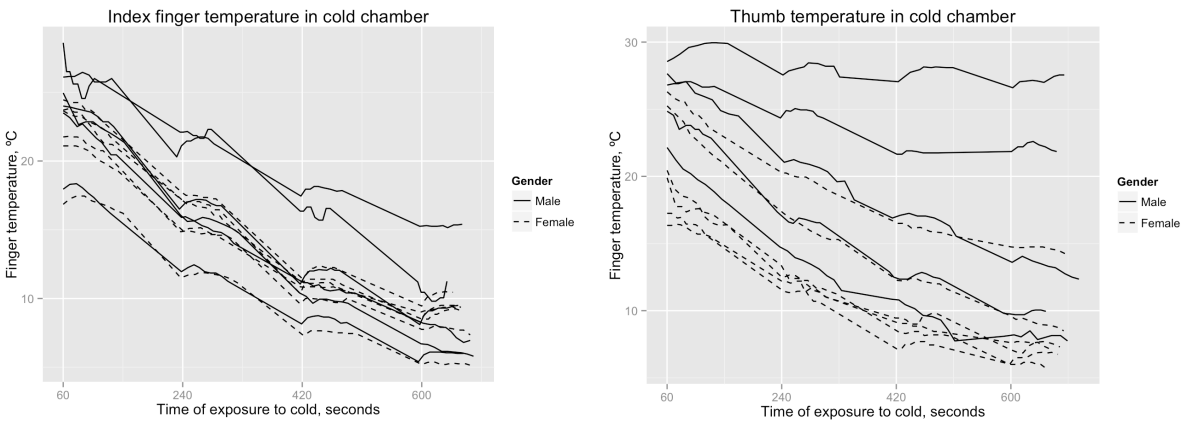

Figure 10. Indicative finger temperature drop when entering the cold chamber for the first time

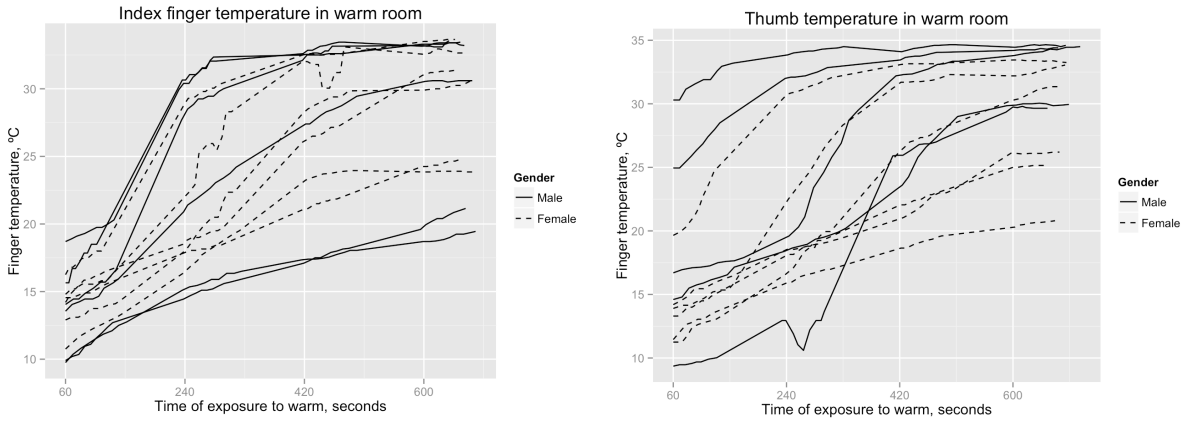

Figure 11. Indicative finger temperature rise when entering the warm room for the first time

4.1.2. Task performance

Mackenzie's software [29] calculates for each 20-task sequence: throughput (using the Crossman & Welford method [74]), error rate, movement time, effective index of difficulty, effective amplitude, and effective width. Outliers from this data were removed as follows:

- One participant (P06) was removed because they made 100% error on the majority of their task sequences (90 task sequences).
- All sequences with error rates over 40% were removed, after analysing the distribution of this variable (589 task sequences). This was done because we manually disabled the recommended outlier removal in the FittsTouch software [41].
- Task sequences with negative or extremely small effective index of difficulty (< 1.6790) were removed, after analysing the distribution of this variable (356 task sequences).

Average finger temperature values were calculated per sequence, and regression analysis was performed for finger temperature and throughput. In the top of Figure 12 we show the underlying trends in the data by visualising all combinations of Amplitude, Width, and Finger (index, thumb).

We next developed a method to analyse this data as a whole. This is not straightforward, because the distribution of finger temperature is skewed towards higher temperatures, leading to fewer data points at lower finger temperatures. For this reason, we decided to bin the finger temperature variable into 5-degree bins (we also used 4 and 3 degree bins with similar results). Then, average values of throughput were calculated per 5 ºC interval (Figure 6, bottom). Using this binned data we perform a linear regression of finger temperature on throughput, which showed a strong fit for index finger $(R^2=0.81, F(1, 5) = 21.09, p < 0.01)$ but not for thumb $(R^2=0.52, F(1, 5) = 5.52, p = 0.07)$. The results indicate that higher finger temperature was associated with higher throughput for the index finger, but not for the thumb. Note that we refer to the active finger, i.e. the finger (index/thumb) used for target acquisition in each block.

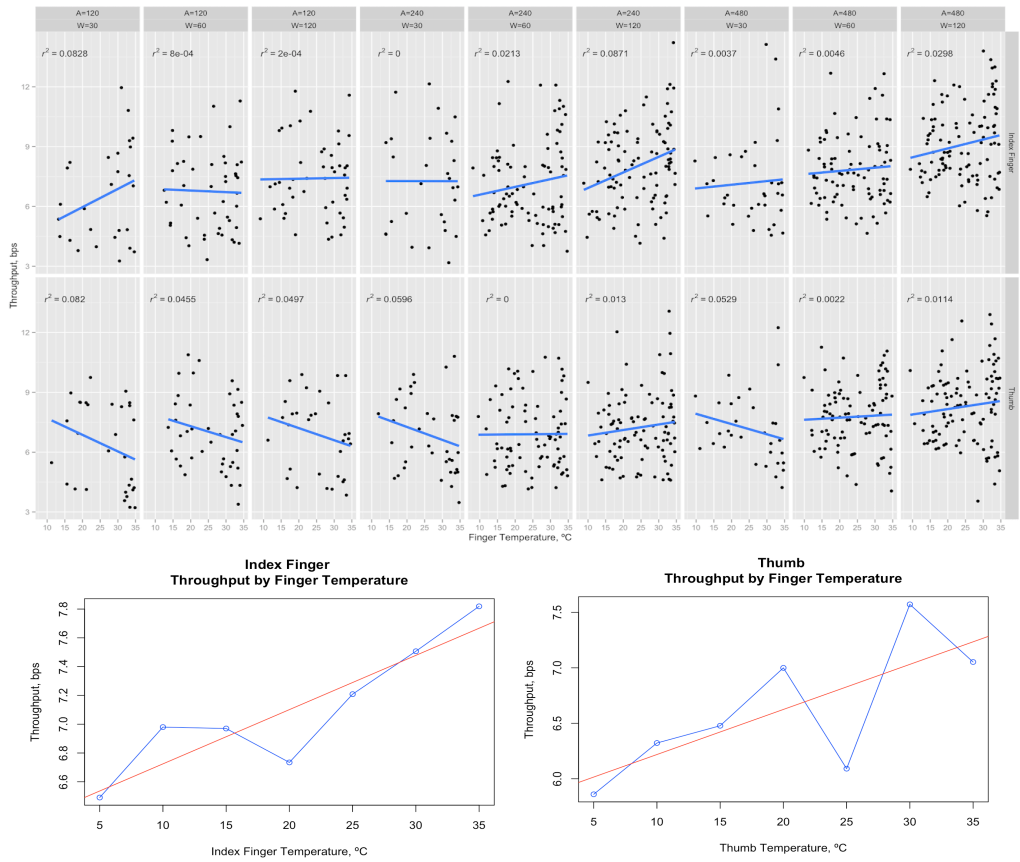

Figure 12. Top: Throughput for each amplitude and width combination by finger temperature. Bottom: Overall throughput by finger temperature

An identical procedure was followed to analyse the relationship between finger temperature and error rate: the underlying trends of the data are shown in the top of Figure 13, while the binned data is shown in the bottom of Figure 13. A linear regression of error rate and finger temperature on the binned data showed a good fit for index finger *(R^2 = 0.71, F(1, 5) = 12.30, p = 0.02)*, but was not significant for thumb *(R^2 = 0.47, F(1, 5) = 4.41, p = 0.09)*. The results suggest that higher finger temperature led to reduced error rates for the index finger, but not for the thumb.

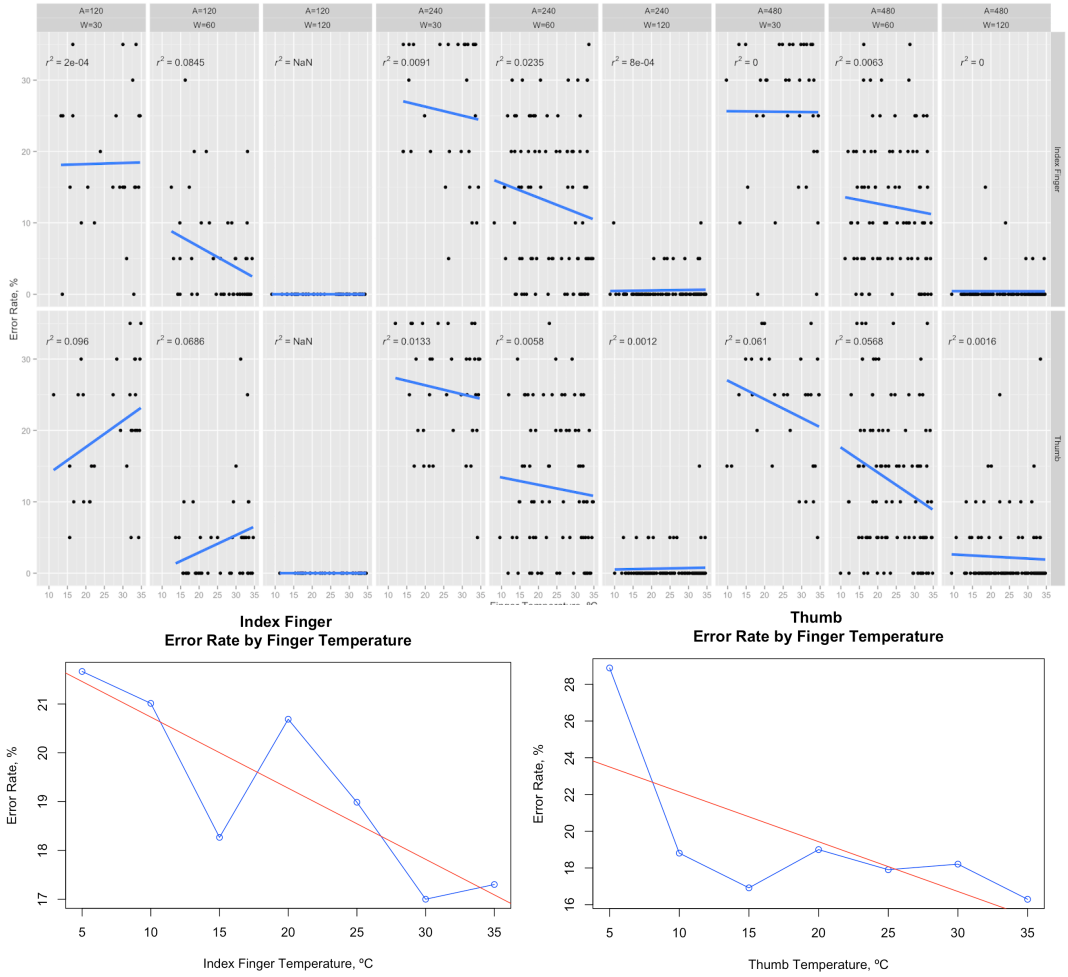

Figure 13. Top: Error rate for each amplitude and width combination by finger temperature. Bottom: Overall error rate by finger temperature

4.1.3. 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 approach as previously (underlying data in Figure 14 top; binned data in Figure 8 bottom), a regression of finger temperature on effective index of difficulty was significant for both index finger $(R^2 = 0.62,\ F(1,5) = 8.62,\ p = 0.04)$ and thumb $(R^2 = 0.61,\ F(1,5) = 7.81,\ p = 0.04)$, suggesting that higher finger temperature leads to higher effective index of difficulty. Note that the definition of effective index of difficulty is $log(A_e/W_e + 1)$, and therefore our results suggest that higher finger temperature is associated with smaller effective width (W_e), i.e. with more accurate performance.

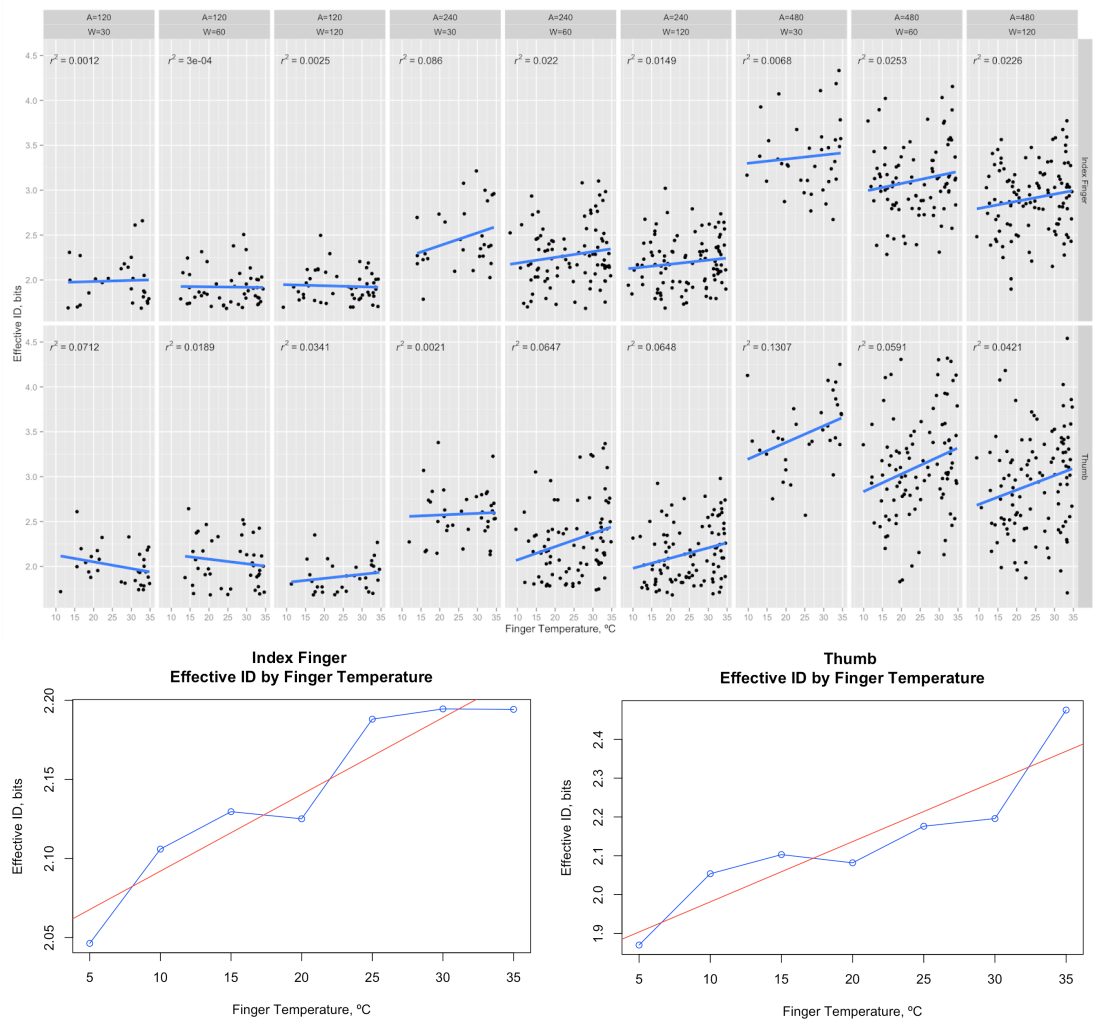

Figure 14. Top: Effective index of difficulty for each amplitude and width combination by finger temperature. Bottom: Overall effective index of difficulty by finger temperature.

We further investigate if finger temperature can be used to predict movement time. A regression of the Standard Model that uses the Crossman & Welford's [74] formulation $MT = a+b*ID_e$ (where ID_e is effective index of difficulty) showed a fit of $R^2 = 0.23$ $(F(1,101) = 29.68, p < 0.01)$ for index finger and $R^2 = 0.39$ $(F(1, 92) = 59.81, p < 0.01)$ for thumb. A regression of our Extended Model using the formulation $MT = a+b*ID_e+c*Temperature$ showed an improved fit for index finger $(R^2 = 0.25, F(1,101) = 33.35, p < 0.01)$ and for thumb $(R^2 = 0.42, F(2,92) = 66.56, p < 0.01)$. Both models are shown in Figure 15 and Figure 16 for index finger and thumb respectively. The coefficients for the extended model are shown in Table 1.

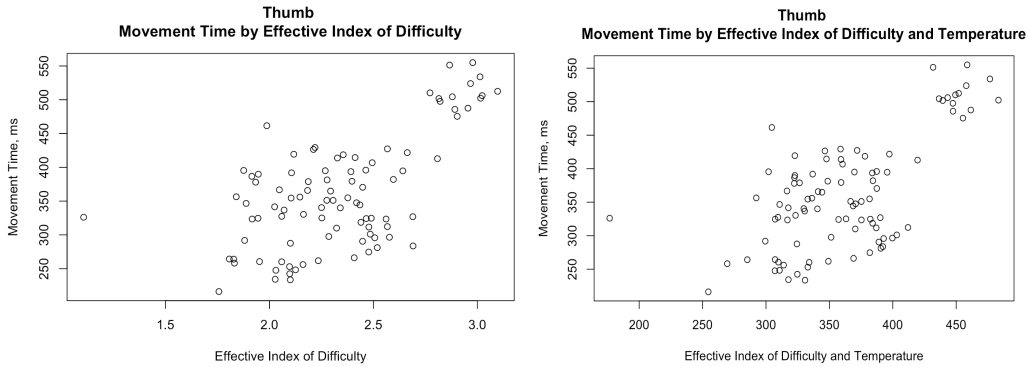

Figure 15. Left: the standard model for predicting movement time ($MT = a+b*ID_e$). Right: our extended model ($MT = a+b*ID_e+c*Temperature$).

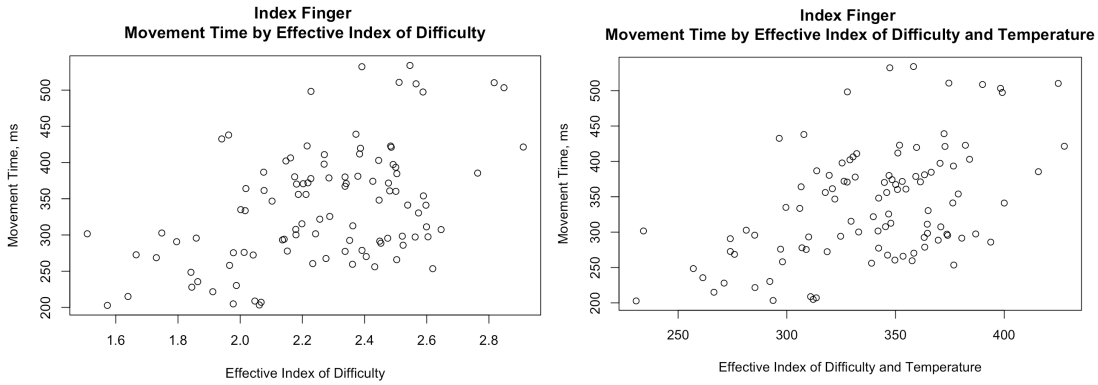

Figure 16. Left: the standard model for predicting movement time *($MT = a+b*ID_e$)*. Right: our extended model *($MT = a+b*ID_e+c*Temperature$)*.

Table 1. Coefficients for multiple regression

		Estimate	**Std. Err.**	**t value**	**p value**
Index Finger	(Intercept)	49.56	55.86	0.89	< 0.39
	IDe	140.83	24.67	5.71	< 2e-07
	Temperature	-1.55	0.93	-1.68	< 0.10
Thumb	(Intercept)	44.77	44.25	1.01	< 0.32
	IDe	151.16	18.66	8.11	< 2.5e-16
	Temperature	-1.78	0.89	-2.01	< 0.05

We note that we also attempted to extend the standard model by reformulating the definition of ID_e ($ID_e = log2(Ae/We+1)$). For instance, we reformulated the definition as $ID_{e1} = log_2(A_e/W_e + 1*Temperature)$ and $ID_{e2} = log_2((A_e*Temperature)/W_e + 1)$, but the resulting model had a poor fit with movement time for both the former (index $R^2 < 0.05, p < 0.03$; thumb $R^2 < 0.10, p < 0.01$), and the latter (index $R^2 < 0.01, p < 0.83$; *thumb* $R^2 < 0.01, p < 0.46$).

4.2. Study 2: Fine-motor and cognitive impairments during mobile interaction in cold environments

The experiment (including intake, training, and experiment) lasted about 90 minutes per participant, and the scientists observed 4 participants per day. Each participant

completed a total of at least 288 correct circles and icons hits. Overall we collected 33,672 target hits from 24 participants for both applications (26,448 for TapCircle and 7,224 for FindIcon), and independent thermal data from 2 fingers per participant every 1 second. All data was timestamped to enable post-hoc synchronisation.

4.2.1. Physiological response

Participants' physiological response is visualized by calculating their finger temperature during the full period of their participation in the experiment for a finger performing the task (Figure 17 and Figure 18). The data is grouped by participant (thumb, index). The finger temperature was gradually dropping when participants were exposed to cold, and was rising when participants were back in the warm room.

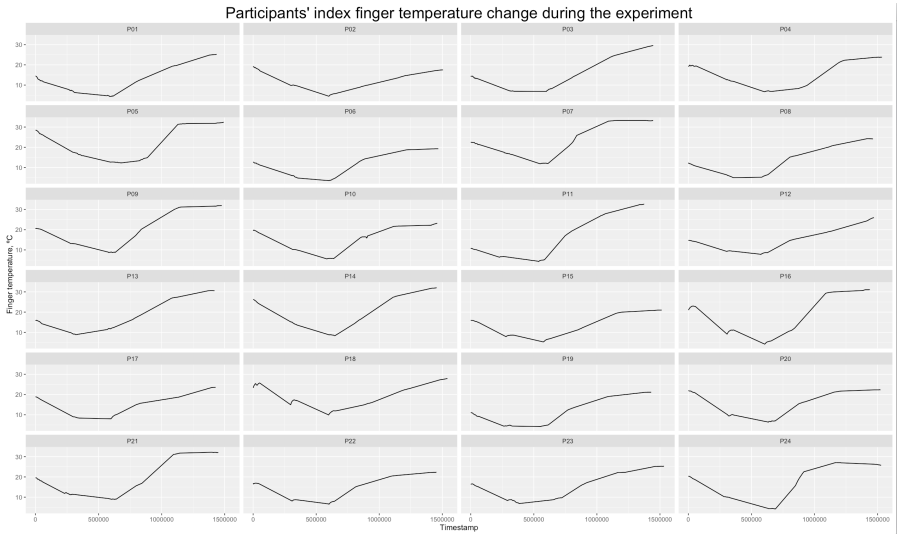

Figure 17. Index finger temperature change during the experimental procedure

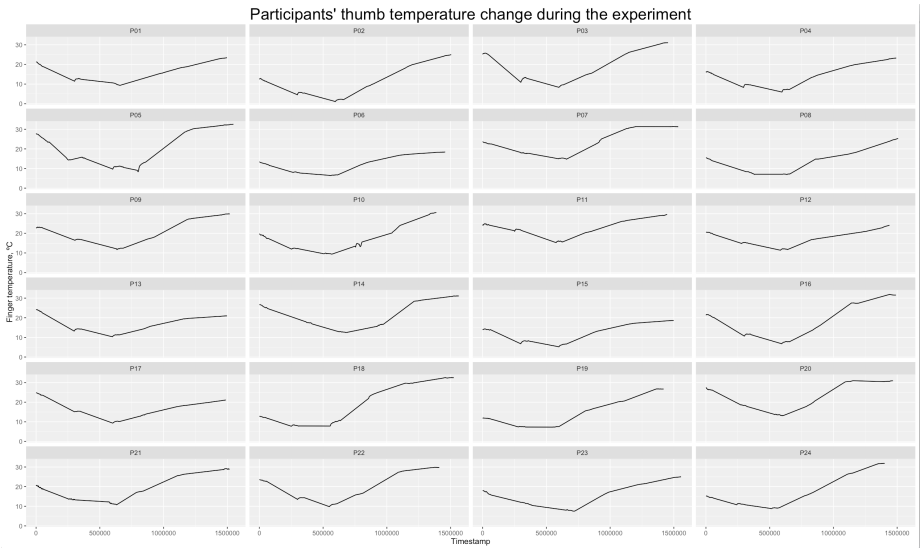

Figure 18. Thumb temperature change during the experimental procedure

4.2.2. Task performance in TapCircles application

A two-way repeated measures ANOVA was conducted to compare the effect of the environmental condition (cold or warm room) and interaction mode (one-handed or two-handed) on the offset between the target centre and participants' click. The results showed a significant effect for both environmental condition $(F(1, 26421) < 6.32, p < 0.01)$ and interaction mode $(F(1, 26421) = 68.26 , p < 0.01)$, and no significant interaction effect $(F(1, 26421) = 0.55, p = 0.46)$.

Mean offsets between target centre and participant click are presented in Figures 19 and 20, with arrowheads indicating the mean direction and mean length of the offset vector. The colours of the circles also indicate the length of the offset, with lighter colour indicating longer offset and darker colour indicating shorter offset. A one-way ANOVA was conducted to compare the effect of the grid position (coded as a categorical variable) on the offset length. There was a significant effect of the grid position on the length of the offset $(F(23, 26421) = 35.40, p<0.01)$. Post-hoc comparisons using the Tukey HSD test indicated that the mean value of offset size for position 0 was significantly longer than the offset size for positions 7, 11, 15, and 19. Further, offset length for position 20 was significantly longer than for all of the other positions.

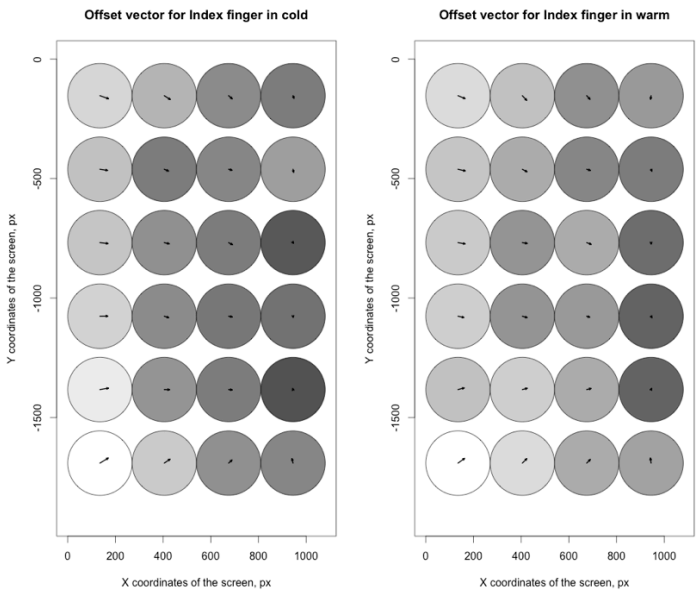

Figure 19. Left: Offset vectors for index finger in cold. Right: Offset vectors for index finger in warm

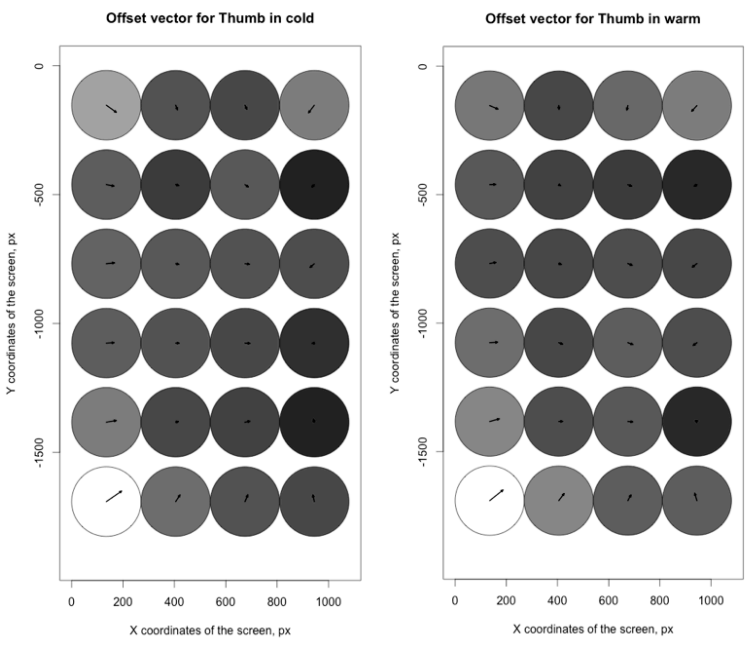

Figure 20. Left: Offset vectors for thumb in cold. Right: Offset vectors for thumb in warm

A two-way repeated measures ANOVA was also conducted to compare the effect of the environmental condition and interaction mode on time taken to tap the circle. The results showed a significant effect for both environmental condition *($F(1, 26421) = 78.76, p < 0.01$)* and interaction mode *($F(1, 26421) = 2908.53, p < 0.01$)*. Furthermore, there was a significant interaction effect between the two factors *($F(1, 26421) = 14.11, p < 0.01$)*.

Finally, a one-way ANOVA was conducted to compare the effect of the grid position (coded as a categorical variable) on time taken to hit the circle. The analysis showed a significant effect of grid position on the time *($F(23, 26401) = 213.10, p < 0.01$)*. Positions 0 and 20 took significantly longer time than all of the other positions. All the positions from 5 to 18 were significantly faster compared to positions 1, 2, 3, 4, 21, 22, 23. Table 2 shows the mean offset and time taken to tap a target in the TapCircle app.

Table 2. Mean offset and time (TapCircle app)

Environment	**Interaction mode**	
	Two-handed (Index)	One-handed (Thumb)
Cold	Offset = 42.66 px Time = 603.68 ms	Offset = 49.30 px Time = 731.99 ms
Warm	Offset = 41.34 px Time = 593.41 ms	Offset = 46.47 px Time = 708.70 ms

4.2.3. Task performance in FindIcon application

Data treatment

We followed the recommendations from Flouris [16] and quantified vigilance using reaction time and error. In the FindIcon application, participants had to complete the task of finding and clicking a target icon, which consisted of three subtasks: 1) memorise the target icon, 2) locate the target icon amongst 24 icons, 3) click on the target icon. The time for subtask 1 was recorded separately by our software. However, the time for subtasks 2 & 3 was inevitably aggregated and recorded as a single value.

To quantify vigilance, we were mostly interested in subtask 2: the time taken to search and locate a particular target icon. Hence, in our analysis we had to develop a way to measure subtask 2 and exclude the time taken to complete subtask 3.

Due to our experimental design, the data from the TapCircles trials gave us an estimate of the average time needed for a participant to click an icon at a particular grid position, using either thumb or index finger, in either the warm or cold rooms. Essentially, this mean value is an estimate for the duration of subtask 3, and therefore we were able to subtract it from our data to arrive at an estimation for subtask 2. We note that different values were calculated and subtracted for each participant, room (warm vs. cold), interaction mode (index vs. thumb), and block (minute 1:00 vs. minute 6:00 vs. minute 11:00).

Time

We analysed if the time taken to memorise each target icon was affected by the environmental condition and interaction mode (Table 2). A two-way repeated measures ANOVA was run to test the effect of the environmental condition (cold or warm room) and interaction mode (one-handed or two-handed) on the time taken to memorise the icon. The results showed a significant effect for environmental condition $(F(1, 6878) = 128.640, p < 0.01)$ but not interaction mode $(F(1, 6878) = 1.179, p < 0.29)$, and a significant interaction effect $(F(1, 6878) = 278.525, p < 0.01)$. In the cold chamber participants were significantly slower in memorising an icon than in the warm room across both one-handed and two-handed interaction modes.

Next, we analysed if the time taken to find an icon was affected by the environmental condition and interaction mode. A two-way repeated measures ANOVA was conducted to compare the effect of the environmental condition (cold or warm room) and interaction mode (one-handed or two-handed) on the time taken to find an icon. The results showed no significant effect for environmental condition $(F(1, 6878) = 2.83, p = 0.09)$ and interaction mode $(F(1, 6878) = 1.73 , p < 0.19)$, and no significant interaction effect $(F(1, 6878) = 0.20, p = 0.66)$. Table 2 presents average values of time taken to find an icon for each condition per interaction mode.

Table 3. Mean time to memorise and time to find icons (FindIcon app)

Environment	**Interaction mode**	
	Two-handed (Index)	One-handed (Thumb)
Cold	Time to memorise = 854.23 ms Time to find = 873.27 ms	Time to memorise = 921.92 ms Time to find = 889.40 ms
Warm	Time to memorise = 814.89 ms Time to find = 833.65 ms	Time to memorise = 874.48 ms Time to find = 866.46 ms

Grid position

We next analysed if the position of the grid affected the time taken to find an icon. A one-way repeated measures ANOVA showed significant effect of grid position on time taken to find an icon *(F(23, 6878) = 10.43, p < 0.01)*. A Tukey HSD post hoc test showed that time to find an icon at positions 0, 1, 4, 12, 16, 22, and 17 was significantly slower than at positions 5, 6, 7, 8, 9, 10, 11. Positions 20 and 21 were significantly slower than positions 2, 3, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 18, 19.

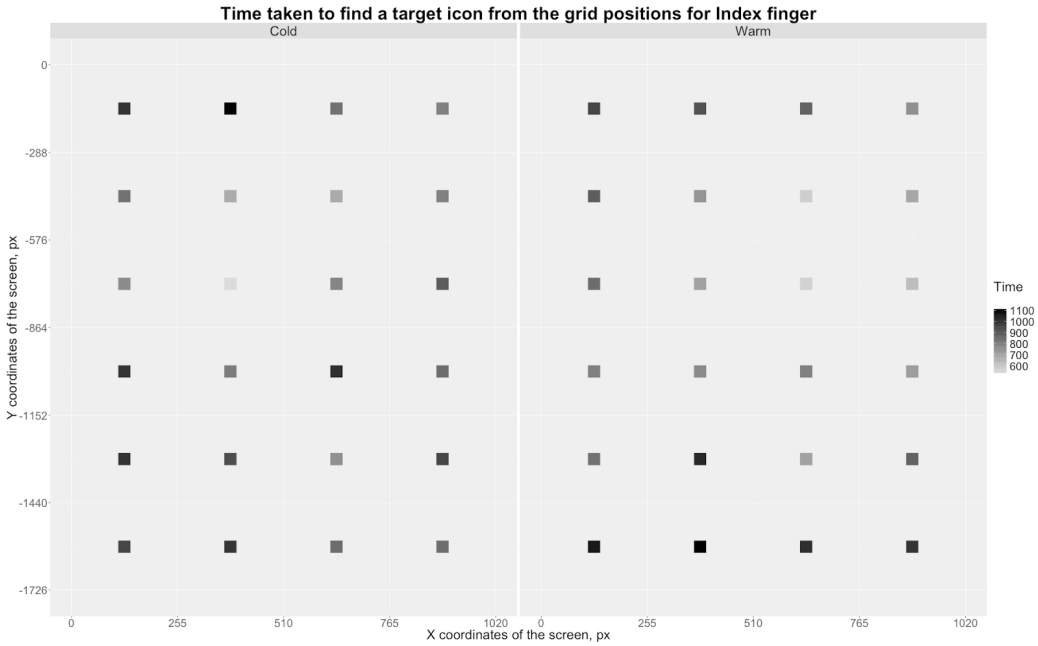

Figure 21. Left: Time taken to fing a target icon on the grid position for index finger in cold. Right: Time taken to fing a target icon on the grid position for index finger in warm

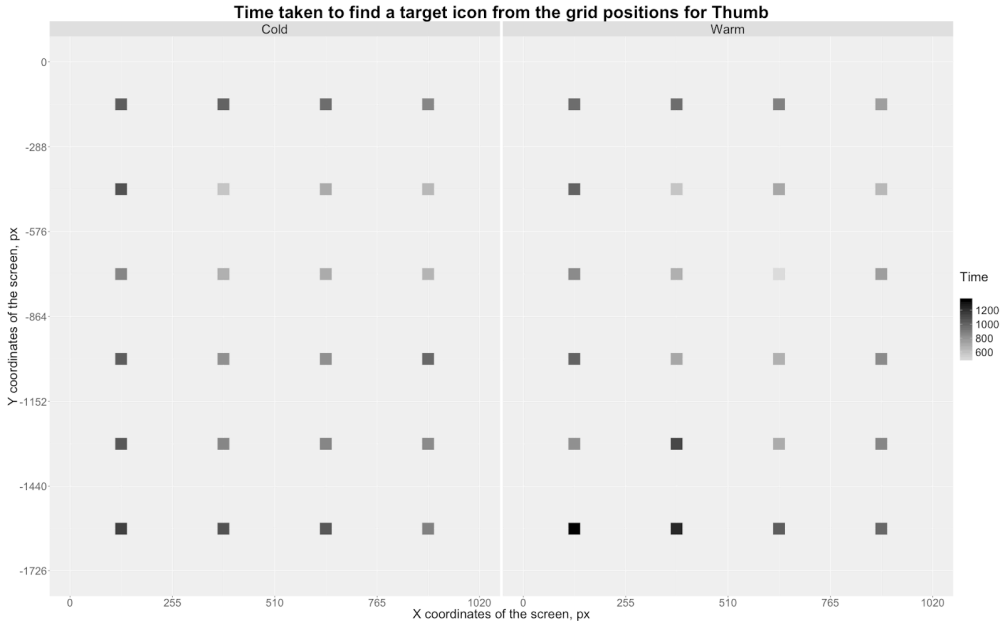

Figure 22. Left: Time taken to fing a target icon on the grid position for thumb in cold. Right: Time taken to fing a target icon on the grid position for thumb in warm

We also investigated if the colour of the app icons, or the app being installed on a participant's phone, affected the time taken to find it. Four researchers rated the icons according to the icons' dominant colours. This classification revealed a taxonomy with 8 categories of colours: blue, red, green, purple, yellow, brown, orange, and mixed (for icons with no dominant colour). An interrater reliability analysis using the Kappa statistic was performed to determine consistency among raters, which showed strong agreement between raters $(\kappa = 0.77, p < 0.01)$. Overall there were 7 blue icons ("Facebook", "Shazam", "Skype", "Dropbox", "Translate", "Messenger", "Twitter"), 6 mixed colour icons ("Drive", "Chrome", "Candy Crush Saga", "Angry birds", "Maps", "Fruit Ninja"), 4 red icons ("Adobe Acrobat reader", "YouTube", "Gmail", "Google+"), 3 green icons ("Line", "WhatsApp", "Hangouts"), and 1 of each: purple ("Viber"), yellow ("TempleRun"), brown ("Instagram"), orange ("ChatOn").

A two-way ANOVA showed a significant effect of icon colour on time taken to find the correct icon $(F(7, 6866) = 34.98, p<0.01)$, no significant effect of the participant having the application installed on their own phone $(F(1, 6866) = 0.04, p = 0.84)$, and no significant interaction effect $(F(7, 6866) = 1.60, p < 0.13)$. A Tukey HSD post hoc test showed that blue icons as well as mixed colour icons took significantly longer time to be found compared to brown, green, orange, purple, red, and yellow.

Modelling the impact of cold exposure

We built a model that describes the effect of cold on the time taken to find and click the target icon. We first ran a stepwise multiple regression analysis to predict the total time taken to locate and click a target icon. The final prediction model contained all 5 possible predictors (environmental condition, interaction mode, x and y centre coordinates of target grid position, and icon colour) and was built in 1 step without any of the variables being removed. The model is statistically significant $(F(11, 6821) = 38.53, p < 0.01)$ and described approximately 5.9% of variance of total time taken to search and locate a particular target icon $(R^2 = 0.059, \text{Adjusted } R^2 = 0.057)$. All factors were statistically significant.

We next built a model that describes the effect of cold on the time taken to find the target icon, i.e. adjusting time to exclude the time needed to click the target icon. The final prediction model contained 4 of the 5 predictors (environmental condition, x and y centre coordinates of grid position, and icon colour) and was achieved in 2 steps by removing one variable (interaction mode). This removal was expected, as time was corrected to exclude the physical component of clicking the icon. The model is statistically significant $(F(10, 6822) = 32.60, p < 0.01)$ and explained 4.5% of variance of time taken to find an icon $(R^2 = 0.045, \text{Adjusted } R^2 = 0.044)$. The factor of environmental condition was not statistically significant within the model ($p = 0.10$) but all other factors were.

Contrasting the two models indicates that when only cognitive effort is considered, the environmental condition and interaction mode become negligible factors in predicting time taken to find an icon.

Error

A Chi-square test was conducted to analyse the relationship between environmental condition and if an error was made when trying to finding an icon, and no significant

relationship was found $\chi^2(1, 1) = 0.12, p = 0.73)$. Similarly, no significant relationship was found between interaction mode and if an error was made when trying to finding an icon $\chi^2(1, 1) <0.01, p = 0.97)$. However, a Chi-square test showed a significant effect of icon colour on if an error was made when trying to finding an icon $\chi^2(1, 7) = 26.32, p < 0.01)$. Participants made more errors when finding blue icons compared to orange and purple. Finally, no significant relationship was found between participants that had installed the application of the target icon they were looking for and if an error was made when trying to finding an icon $\chi^2(1, 7) < 0.01, p = 0.96)$.

4.2.4. Interview results

During our interviews the majority of participants (16 out of 24) felt they were less precise in cold rather than in warm, while performing the tasks on TapCircle application. When asked for the reason, sense of cold and numb fingers were the main ones named: *"I was less precise in cold, because my fingers were numb" (P14), "The precision was slightly worse in the cold due to frozen fingers" (P20), "My peak physical performance is more adjusted to warm" (P09).* Interestingly enough 6 out of 24 participants thought they were equally precise in both cold and warm conditions. Moreover, two participants thought they were more precise in the cold than in the warm, "because wanted to get the task done, hence focused on pressing the circles". Overall, this subjective opinion is inline with our findings that showed that in the cold they were less precise than in the warm. When asked about particular positions on the screen that took longer time to access in a one-handed interaction mode (thumb finger), most participants agreed that corners of the screen along with the left side edge of the screen were the most difficult ones to access, hence required more time. Again, their answers correspond with our quantitative findings, indicating the top left and bottom left corners as the slowest to press.

As for the FindIcon application, when asked what strategy they used to find the target icon, all but one participant answered that the colour was the major aspect. Moreover, some participants elaborated on the colour aspect of the icons by saying *"Fruit Ninja and Candy Crush icons were more difficult to find because they were colourful" (P17)* or *"their colour was too messy" (P11).* Several participants mentioned that blue icons were harder to find, since there were a high number of them, however 7 people claimed that the Facebook icon (blue) was very quick to find, 3 people claimed Shazam and Skype icons were quicker to find "because of the colour contrast". Our quantitative findings also showed significant higher time taken to find blue and mixed coloured icons.

Furthermore, when asked to elaborate on their search strategy, 10 participants said that they "scanned the screen as a whole", 7 participants preferred "scanning the centre first", and 4 scanned "top, then bottom". One of the participants noted that "When the icon was in the middle, I could directly see it", even though his strategy was to scan icon by icon starting from the top of the screen. The remaining participants reported not having a preferred search strategy. When asked to mark on the grid where it was quicker to find an icon, participants were consistent in selecting the centre of the grid. These results correspond to our findings, which showed that corners of the grid (positions 0 and 20 especially) as well as the top and bottom parts of the grid took longer time to access and find an icon.

5. DISCUSSION AND LIMITATIONS

A decade ago Wobbrock described four trends in society and technology that have direct consequences for mobile interaction, one being the increasing amount of personal computing used away from the desktop [75]. This is because the context of mobile device use can vary substantially more than desktop computers [75]. Hence, dealing with situational impairments [61] of mobile use is an important, but often neglected research challenge. In this work, we explore one example of a situational impairment, mobile interaction in cold environments.

5.1. Fine-motor performance with mobile phones in cold climates

Our first experimental study examined the effect of finger temperature on user performance in completing pointing tasks in the context of a Fitts' law study. In our study we found that finger temperature significantly affected user performance in two-handed operation (i.e., using index finger). In this mode, users with warmer fingers had higher throughput and lower error rates. These findings are partially corroborated by previous research that reports an effect of cold fingers on movement time, but did not establish effect of cold hands on error rate [5]. One potential reason why this effect was not as strong in one-handed operation (i.e., using thumb) is that the movement of the thumb is more limited since the hand has to successfully complete the prehensile task of securing the phone, which defines the base for the thumb to complete the tapping tasks [68]. The distribution of muscles acting on the thumb make it most suited for grasping activities [7], and the functional area of the thumb is much smaller when compared to a dual-handed interaction [4]. In other words, the increased motor difficulty in completing the tasks using the thumb may have had a more significant impact on performance than finger temperature. Nevertheless, a weaker effect may be present which would be likely to be identified with a larger set of participants and more data points for colder finger temperatures ($p = 0.07$ and 0.09 for throughput and error rate respectively).

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 pointing task to examine how people's behaviour 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 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 [26,77].

Finally, we also attempted to extend Fitts' law formula for movement time. The model we propose includes finger temperature parameter as a parameter and gives about 8% relative improvement (2/23 for index and 3/39 for thumb) in comparison

with the original model. The significance of this improvement implies that the temperature parameter is important for movement time calculation and should be accounted in Fitts' law formula.

Our second experimental study's findings show that participants were more precise in a TapCircle task in the warm room than the cold chamber. Previous work has showed that since users cannot feel the position of touchscreen keys or buttons, offsets for top left corner naturally shift towards the lower-right corner, and offsets for lower-right corner naturally shift towards the top-left corner [27]. Our results correspond with these findings and show that the offset skew is observed in both interaction modes, a factor that was not investigate in previous work [27].

Our results also demonstrate for the first time that the magnitude of the offset is larger in cold conditions, particularly in one-handed interaction mode. While the differences in offset may look relatively small between the two environmental exposure conditions (Table 1), these are likely to be exacerbated in repeated everyday phone use in cold environments, especially when we consider that target acquisition is a task that users repeatedly perform to interact with touch-screen devices.

In terms of time taken, participants' performance also dropped in the cold chamber. Again, the differences in one-handed interaction mode were more pronounced in the cold chamber. Taking into account the simplicity of the task, we argue that a more complex task, such as text entry or object manipulation, would lead to even higher differences between these two environmental exposure conditions. Moreover, several participants were not aware of their precision loss during their interaction with the mobile device, since in the interview sessions 25% of participants (6 out of 24) claimed they were equally precise in both cold and warm rooms. This example highlights the importance of passively identifying potential situational impairments so that the device can react independently of users' direct feedback.

Further, we highlight the effect of grid position on the time taken to tap a circle. Our findings agree with previous work by Park & Han [53], but extends to both modes of interaction, since Park & Han primarily considered one-handed thumb interaction. According to our findings, the corners of the screen and the upper & lower edges of the screen are areas where it was harder to tap a circle. Given that in cold settings users' fine-motor skills deteriorate, these challenging areas of the screen become even harder to reach/press.

Our results provide an empirical basis to design devices and interfaces that adjust to better accommodate situational impairments caused by cold exposure [75]. This can be achieved on mobile phones by increasing the size of buttons in problematic areas of the screen, or activating accuracy-improving input techniques such as Fat Thumb [6] or GraspZoom [46].

5.2. Cognitive performance with mobile phones in cold climates

Unlike physical performance, deterioration of cognitive skills tends to occur after a longer time of exposure to cold. For example, Flouris *et al.* recorded adverse deterioration of vigilance after 45 minutes of exposure to cold in -20 ºC, and was highly correlated to core body temperature [16]. In addition, several studies state that cognitive impairment happens when the core body temperature drops by 2 – 4 ºC, which can require longer exposure to cold [9,18,40]. Hence, it is natural to argue that shorter exposure to less extreme ambient temperatures many not have any significant

effect on vigilance. Our study did not control for core temperature as this would require invasive methods of measurements and would therefore not represent realistic use conditions.

The effect of cold on recall and recognition is disputable, since deterioration in recall but not recognition was observed in some studies [2], contrary to other studies where decline in recognition but not recall was reported [14]. Our findings demonstrate that in the cold room participants took significantly longer time to memorise an icon compared to the warm room, however the following subtasks were not significantly affected by the cold environment. Neither time, nor frequency of errors were significantly affected by cold exposure, and our results correspond to the results by Flouris et al [16]. Another possible explanation beyond insufficient exposure time to cold may have been that the task was too simple to measure and record a significant drop in vigilance. However, it is also unlikely that in cold users would perform complex tasks on their mobile devices. We also avoided using text entry as a task due to the difficulty in distinguishing the timing for its cognitive and physical components.

Nonetheless, our results demonstrate a significant effect of grid position on the time taken to find an icon. The screen's corners and upper/lower edges require more time to find an icon, in comparison to central positions. This finding suggests that future work can consider how people search mobile screens, ideally with the use of an eye tracker. While prototypes that detect eye motion when using mobile phones exist [8,45], to the best of our knowledge, no prior work has investigated favourable mobile screen areas for the human eye in this manner. Such work could also help to understand mobile interface design implications for users with visual impairments, if prioritised areas of user gaze were identified.

Similarly, our results show a significant effect of icon colour on time taken to find an icon and frequency of errors. Interestingly, icons with the most predominant colour (blue) and mixed colours took participants longer time to identify an icon, while blue icons were also more prone to errors. As colour is a fundamental aspect of human perception [43], it is important to mitigate its adverse effect on cognition, especially if cognition is being affected by the environment. Unfortunately, most of the existing studies focus on two or three primary colours [12,43,63], whereas in our study we had 8 defined colours for the icons. Our results suggest that the choice of colour can have a much more pronounced effect than ambient temperature. Crucially, this means that poor colour choices can be worse than freezing temperatures, at the levels explored in this work, in terms of cognitive performance during mobile interaction.

Finally, the comparison of the two predictive models we have presented indicates the significance of environmental condition on physical impairment, but not cognitive. Due to the time correction in the second model, the physical factors were no longer significant (environmental condition and interaction mode). This is an important finding of our study, because it implies that designers should prioritise adjusting mobile interface designs in cold environmental conditions to improve physical interaction with mobile devices. Further, it shows the importance of accounting for physical factors when conducting experiments aimed at assessing cognitive performance.

5.3. Adapting mobile interfaces to cold climates

Our findings from the first experimental study imply that user performance when using mobile devices depend on user's finger temperature, hence it should be considered as a factor for interface adjustments on mobile devices. Unfortunately, cold research is somewhat lacking within the HCI community [24,56,78]. Previous work on the effect of cold fingers on technology use and our own results indicate that technology interfaces should not follow universal design rules when considering colder climates. 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.* [6]. 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 behavioural 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, such as detecting ambient temperature, time of exposure to cold and location, and might be common in the future, given the fact that mobile research is shifting towards sensing [39] for example phone battery temperature could be used as an indicator to detect cold environments. Also, people lose heat at different rates, as can be seen from Figures 4, 5, 17, and 18 and their performance varies, therefore it is important to consider personal behavioural patterns in adaptation.

When loss in input performance is detected, it can be useful to adapt the mobile interface. The loss of manual dexterity in the cold can be considered to resemble behaviour 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 [50,67,80]. For example, Nicolau *et al.* [50] recommend to have tapping as the main interaction method meaning that swipe gestures should be scarcely or not at all used. Guerreiro *et al.* [23] have found that people with motor-impairments find it is easier to select targets at the bottom of the screen. Therefore, target position could favour 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 [1,49,67] and enhance the touch area [80]. In addition, voice-to-text and voice control options of mobile devices would be favoured not only by motor-impaired people [49], but also could be applicable for using mobile phone in cold temperatures. 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, recognise behavioural patterns and adapt accordingly. A similar idea for personalisation was suggested by Goel *et al.* [19] 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.

5.4. Limitations

Both of our experimental studies had several limitations. For example, in the first experimental study 1 we tested only one type of task, which was one-dimensional target acquisition. Moreover, in both of the studies the task was constrained to be accomplished either by an index finger or a 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.

Another limitation was that some participants might have been more acclimatized to cold climate conditions, for example were born in Nordic countries. Moreover, other factors 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.

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 [5] 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. CONCLUSIONS AND FUTURE WORK

To conclude, the work presented in this Thesis investigated the effect of a cold environment on smartphone input performance, and general fine-motor and cognitive skills. Our results show that cold adversely affected participants' smartphone input and fine-motor skills performance, but not vigilance.

Our first experimental study describes a controlled laboratory experiment on the effect of cold temperature on smartphone usage, and particularly on target acquisition. 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 operation. Finally, we demonstrate that the use of finger temperature can improve 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 literature can be considered as a countermeasure. 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 touch-screen and keyboard-based), smartphones (touch-based and keyboard-based), and potentially wearable technologies (smart watches, and smart glasses, skin conductivity systems, augmented reality). Finally, as we have established that temperature affects input accuracy and error rate on smartphones, new and optimised interaction techniques can be explored, to automatically adapt smartphone input capabilities when in cold temperatures.

Our second study investigates the effect of cold temperature exposure on mobile interaction in one-handed (using thumb) and two-handed (using index finger) interaction modes with bare hands. We find that in cold, fine-motor skills are significantly affected during mobile interaction; however the effect on cognitive performance is not significant. Specifically, in a cold environment the touch accuracy decreases, the target acquisition offset is significantly longer across both interaction modes, and participants take significantly longer time to hit a target. Further, cognitive skills measured by time taken to find a target icon and error frequency are not significantly affected by the environmental condition, but are substantially affected by the colour of an icon and the location on the 4x6 screen grid. We also highlight that when investigating performance of cognitive tasks on mobile devices it is important to correct time measurements to account for fine-motor movement and dexterity.

Our findings highlight the need for mobile interfaces to adapt for usage in cold settings, especially considering fine-motor skills. For example, current smartphone input techniques for users with disabilities can be extended to cold environment scenarios. Future research is needed to investigate and identify not only the effect of cold but other situational impairments that can cause fine-motor and cognitive deterioration when using mobile technologies.

Overall, our work provides a significant contribution to HCI research, particularly regarding the design of mobile interfaces, since we demonstrated that interaction with a mobile device is adversely affected by a cold environment. To the best of our knowledge, it is the first research work targeted to study mobile device interaction in cold, and it used a novel approach of correcting measurements when investigating performance of cognitive tasks to take into account the physical element of the task.

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