Quantifying the Effects of Situationally-Induced Impairments and Disabilities on Mobile Interaction

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Submitted in total fulfilment of the requirements of the degree of

Doctor of Philosophy

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February, 2020

Abstract

Situationally-Induced Impairments and Disabilities (SIIDs), also known as situational impairments, have been shown to negatively affect mobile interaction. This is a consequence of the fact that smartphones have become an indispensable part of our everyday life, and are used under various situations, contexts, and environments. While some situational impairments have received more attention from the research community (*e.g.,* walking-, encumbrance-based SIIDs), some remain underexplored. In addition, research conducted on SIIDs has typically followed an ad-hoc approach, with studies aimed at investigating the impact of a particular SIID on a particular task.

Conversely, this thesis systematically quantifies the effects of a range of SIIDs: ambient noise, stress, and dim ambient light on mobile interaction. These findings then enable us to draw baseline comparisons between the effects of these SIIDs on mobile interaction. Furthermore, in a case study this thesis focuses on cold-induced SIIDs, and proposes a sensing mechanism to detect and respond to the onset of such effects.

Our contribution to Human-Computer Interaction (HCI) and UbiComp research is to enhance our understanding of the impact of SIIDs on mobile interaction. This knowledge is crucial to enable the development of smarter ubiquitous technology that can detect SIIDs and adapt mobile device interfaces accordingly with the purpose of improving the user experience for people of all abilities.

Declaration

This is to certify that

1. The thesis comprises only my original work towards the PhD.
2. Due acknowledgement has been made in the text to all other materials used.
3. Appropriate ethics procedure and guidelines have been followed to conduct this research.
4. The thesis is less than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Zhanna Sarsenbayeva

February 2020

Preface

This thesis has been written at the School of Computing and Information Systems, The University of Melbourne. The major parts of this thesis are in Chapters 4, 5, 6, 7 and 8. Ethics approval for the studies presented in Chapters 4, 5, 6 were obtained from The University of Melbourne Human Ethics Advisory Group. The study presented in Chapter 8 was conducted at the Finnish Institute of Occupational Health in collaboration with the colleagues from University of Oulu, Finland, under local ethical guidelines. Chapters 4, 5, 6, and 8 are based on peer-reviewed publications and I declare that I am the primary author and have $> 50\%$ contributions in each of the following publications:

1. Zhanna Sarsenbayeva, Niels van Berkel, Eduardo Velloso, Vassilis Kostakos, and Jorge Goncalves. 2018. Effect of Distinct Ambient Noise Types on Mobile Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 2, Article 82 (July 2018), 23 pages.
   Ethics ID: 1750350.1, The University of Melbourne Human Ethics Advisory Group.

2. Zhanna Sarsenbayeva, Niels van Berkel, Danula Hettiachchi, Weiwei Jiang, Tilman Dingler, Eduardo Velloso, Vassilis Kostakos, and Jorge Goncalves. 2019. Measuring the Effects of Stress on Mobile Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 1, Article 24 (March 2019), 18 pages.
   Ethics ID: 1851997, The University of Melbourne Human Ethics Advisory Group.

3. Zhanna Sarsenbayeva, Niels van Berkel, Weiwei Jiang, Danula Hettiachchi, Vassilis Kostakos, and Jorge Goncalves. 2019. Effect of Ambient Light on Mobile Interaction. In *IFIP Conference on Human-Computer Interaction* (pp. 465-475) (September 2019). Springer, Cham.
   Ethics ID: 1852612, The University of Melbourne Human Ethics Advisory Group.

4. Zhanna Sarsenbayeva, Niels van Berkel, Aku Visuri, Sirkka Rissanen, Hannu Rintamaki, Vassilis Kostakos, and Jorge Goncalves. 2017. Sensing Cold-Induced Situational Impairments in Mobile Interaction Using Battery Temperature. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 98 (September 2017), 9 pages.

In addition, I would like to acknowledge the following sources of funding that supported my research:

- Google PhD Fellowship in Human-Computer Interaction
- Melbourne Research Scholarship
- Diane Lemaire Scholarship
- University of Melbourne-University of Manchester Research Fund
- Google PhD travel grants
- UbiComp'18 travel grant

Acknowledgements

I was very lucky to share my PhD journey with people to whom I am grateful and would like to express my appreciation.

First and foremost, I would like to thank my primary supervisor Dr. Jorge Goncalves. I have so many things that I am eternally grateful for, I don't even know where to start. Thank you for your wise guidance throughout my PhD journey. Thank you for being so invested in my research life and academic career. I could share with you my challenges and worries that I was going through and always received support that helped me strive through these difficulties. I honestly could not have dreamt of a better supervisor. Thank you for always being there for me (even when you were not attending my talks, but asked people to record them to watch later :)). Thank you for your sharp thinking and insightful reflections and thought-provoking questions that have expanded my mind and thanks for challenging me by involving in various research activities and projects. They definitely made me a better researcher and a better person. Thank you for being not only a great supervisor, but also a great friend.

Then of course my infinite gratitude goes to my secondary supervisor Professor Vassilis Kostakos. Thank you for the opportunity to do research with you. Thanks for taking me on board with you in your Australian adventure. Thank you for our insightful discussions and inspiring meetings. Thank you for believing in me, as it all started back in Oulu, Finland when you hired me as a Research Assistant. Thank you for your endless support and optimism. I am forever grateful.

Next, I would like to express my appreciation and gratitude to my good friend Niels van Berkel (Dr. van Berkel now). Niels, you have been my main support as well as the major source of joy and fun during my PhD journey. Thank you for always being there for me and helping to go through the challenges I encountered in my research and personal life. You have been there with me when we moved from Finland to Australia, you have been there with me through the accepts and major revisions, and you have been there with me when travelling for conferences. My PhD life would have been empty without your presence in it. Thank you from the bottom of my heart :)

I would also like to thank Dr. Eduardo Velloso, Dr. Tilman Dingler, and Dr. Benjamin Tag for their support and advice regarding my research and career. Eduardo, thank you for your optimism, kindheartedness, and for the insights I received during our discussions and ideation. Thanks for the morning maths, stats, research and other knowledge quizzes that you engaged us while getting our morning coffee. Tilman, thanks for being such an endless source of energy, enthusiasm and encouragement which motivates us all in the lab. It is impossible to be sad or lazy when you are around. Thank you, Ben, for being not only a great colleague, but a great friend with whom I could share my secrets and concerns. Your friendship and support mean a lot to me. Thank you all for your support and kindness.

Then, I am deeply grateful to Prof. Timo Ojala from the University of Oulu for his support in my career and of course for creating the International Master's Degree Programme in Computer Science and Engineering which was the start of my research career and defined my further academic path. Thank you for your kindness and support that you provided me with during my studies and research at the University of Oulu. I am honoured to have worked in your research center.

I would also like to thank my colleagues in Finland who witnessed initial steps of my academic career – Dr. Simo Hosio, Dr. Denzil Ferreira, Dr. Aku Visuri, Dr. Simon Klakegg, Dr. Susanna Pirttinkangas, Dr. Heli Koskimäki, Professor Hannu Rintamäki, and Dr. Sirkka Rissanen. Thank you, Simo, for your support, kindness and encouragement throughout my PhD. Thank you for your sincere happiness for my success. Thank you, Denzil, for your insightful discussions, enthusiasm, and motivation. Thank you, Aku and Simon, for your friendship and fun that we have shared back in Oulu. Also thanks for providing us with accommodation at UbiComp'17 :) Big thanks to Susanna and Heli for being great conference companions! Thank you Professor Hannu and Sirkka for your kindness and warm welcome to your lab during our collaborative work in the cold chamber! I love you all for your kind hearts and sincerity.

During my PhD I was lucky to work with academics from other labs outside Australia and I would like to thank them for collaborating and working with me on different projects. My thanks goes to Dr. Sarah Clinch and Prof. Simon

Harper for organising such a warm and welcoming visit for me in their lab at the University of Manchester during my research visit in 2018. I would also like to thank my friends that I got to know in their lab: Olu, Julia, Alan, Aitor, Julio, Deemah, and Alaa. Thanks guys for making my stay in Manchester pleasant and fun!

I would also like to thank Prof. Hans Gellersen for hosting me at Lancaster University. It was such an inspiring experience to visit your lab and learn about your projects.

Then I would like to thank my dear friend and colleague Katerina Mangaroska. Thank you, Katerina, for your care and support you provided me with when it was needed. Thank you for always being there for me. Thank you for introducing me to Prof. Dragan Gasevic to whom I am deeply grateful for his guidance and advice regarding my career in research and academia. Thank you, Dragan, for encouraging us to believe in ourselves and strive higher.

Next, I would like to thank Dr. Garreth Tigwell for being a great co-organiser of our workshop at CHI'19 and for your help to arrange my visit and stay in the UK to be as smooth as possible. My gratitude goes to Prof. Annalu Waller OBE and Dr. Rachel Menzies for organising my visit to the University of Dundee. I would also like to thank Prof. Yeliz Yesilada, Prof. David Flatla, and Dr. Benjamin Gorman for co-organising a great workshop at CHI'19 with me and Garreth. I am happy and grateful that the workshop at CHI brought us all together.

I am also grateful to Prof. Jacob Wobbrock for not only being a great co-organiser of the same workshop at CHI'19, but also for the inspiration of my PhD topic. Your paper "The future of mobile device research in HCI" inspired me to define the topic of my PhD when I was just about to complete my Masters degree. Since then you have been my research role model and someone to look up to when I needed to seek for motivation. Thank you.

Next, I would like to thank the faculty and staff of IDL and CIS at the University of Melbourne. Thank you Prof. Frank Vetere for warm welcome in IDL when we first joined, Assoc. Prof. George Buchanan for the opportunity to serve as an SV Chair at OzCHI'18, Dr. Nicole Barbee for keeping IDL running and for taking care of everyone in the lab, Dr. Greg Wadley, Dr. Jenny Waycott, Dr. Dana McKay, Dr. Melissa Rogerson, Dr. Steven Baker, Dr. Ryan Kelly, Julie Ireland, Rhonda Smithies, Emma Russo, Imbi Neeme for a pleasure to work with you all.

Then I would like to thank my peers and friends in IDL and CIS at the University of Melbourne. Thank you Chu for also being there with me during our move from Finland to Australia. Thanks to Danula, Gabriele, Weiwei, Chaofan, Senuri, Brandon, Martin, Difeng, Kangning, Romina, Sarah, Yousef, Jing, Namrata, Henrietta, Ebrahim, Xin, Hank and many others for sharing fun times during our lunches, dinners, deadlines, trips, and parties. Special thanks to Joshua and Qiushi for helping me to move from one place to another and for assembling my furniture :)

I would also like to thank everyone that I have met at summer schools and conferences and became friends with. Thank you Daniel, Sven, Phillip, Crystal and Callum, Yomna, Florian, Hristian and Martin, Lars, Vito and many others whom I forgot to mention. Also sorry for omitting your "Dr." titles :)

I would also like to thank my friends Anna, Donia, Mitra, Nanci, Esmeralda, Kasia, Iiulia, Inkar, Bakytzhan, Gulsum, Samal, Akbota, Kuralai, Karla, Kamil, Alina, Saniul, Nat, Myran, Shanon, Bibigul, Arian, Artur, and many others for their support and joy we shared together.

Finally, I would like to thank my mom and dad, and my sisters for their unconditional love and tremendous support that they have been providing me with throughout my life. Thank you for supporting me in every step I take, even if it takes me to the other side of the world far away from you. I miss you dearly and I love you.

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Chapter 1

Introduction

1.1 Motivation

The general term of *Situationally-Induced Impairments and Disabilities* (SIIDs), also known as *situational impairments*, refers to the relationship between the user, the surrounding situation\context\environment, the task the user is engaged in, and the technology used to complete this task [242, 243]. Wobbrock clarifies the differences between *Situation*, *Context*, and *Environment* by specifying that the situation refers to the "immediate circumstance" of the user; while context encompasses the broader narrative that includes the user's engaged activities, purposes, goals, and motivations behind these activities [270]. Finally, environment withholds a larger setting, including both the physical and social dimensions [270]. Based on these clarifications, Wobbrock states that the notion of SIIDs comes from the "conviction of situational impairments" – *functional limitations experienced by a user in a specific circumstance*, and from the concept of "situational disabilities" – *task or activity limitations experienced by a user in a specific circumstance* [270].

In this thesis the terms SIIDs and situational impairments are used interchangeably, and are considered in the context of *mobile interaction* on a smartphone. The ubiquitous nature of mobile devices brings new challenges to research on SIIDs as people use them under different situations, contexts, and environments. For example, it is common for modern smartphone users to interact with their devices on-the-go, under the bright sunlight or a dim environment, outside in a noisy street in winter, and even perhaps while carrying luggage or a handbag in one hand. However, this flexibility comes at a cost to users' cognitive, perceptual, motor, and social abilities [270].

The experience of situational impairments during mobile interaction applies to users of all abilities [270]. In other words, both able-bodied and permanently-impaired user groups are negatively affected by SIIDs during mobile interaction. Further, several researchers mention that SIIDs might have temporary detrimental effects on user abilities during mobile interaction similar to the effects of permanent health-related impairments [179, 274]. For example, Yesilada *et al.* demonstrated in their work that a situationally-impaired user without physical impairments performed a similar number of errors on a mobile device as a user with physical impairments [279].

Furthermore, several studies report that situational impairments aggravate the negative mobile interaction experience for permanently-impaired users [1, 112]. For example, visually-impaired users found it challenging to use their smartphones while walking, carrying bags, being in a moving vehicle, being exposed to bright/dim lights or inhospitable weather conditions, navigating in an unfamiliar environment, or while multitasking [1, 112]. Motor-impaired smartphone users also found it challenging to interact with their device while being situationally-impaired [175]. To be precise, motor-impaired users identified challenges to interact with their devices while "on-the-go", due to restrictive clothing, and inhospitable weather conditions [175]. Hence, finding solutions to accommodate SIIDs during mobile interaction will benefit both able-bodied users and users with permanent impairments.

In order to investigate SIIDs, research on the topic has been conducted in four main areas: Understanding, Sensing, Modelling, and Adapting [256].

- **Understanding** focuses on investigating and establishing the effects of SIIDs on mobile interaction.
- **Sensing** concerns itself with designing and building mechanisms that detect SIIDs.
- **Modelling** is directed to model the user, user behaviour, and/or the environment that might occur during SIIDs.
- **Adapting** aims at creating adaptive interfaces to mitigate the effects of SIIDs.

We consider *Understanding* to be the quintessential step that empowers conducting successful research in SIIDs. It is crucial to first understand the exact effects that contextual factors have on mobile interaction. This knowledge can provide the necessary evidence demonstrating if there is a need to build sensing mechanisms, and how to apply modelling and adapting techniques to accommodate these situational impairments, without wasting unnecessary resources. Not only is it important to establish the effects of various SIIDs on mobile interaction, but it is also crucial to be able to compare these effects between each other [235]. By doing so, we can contribute to accumulating knowledge within a specific research topic – an important challenge for HCI and UbiComp research [140,141]. As a result, this research is able to provide further prospects for designers and researchers to prioritise the accommodation of different SIIDs based on the user's current task. A fair amount of research has been conducted to study and understand the impact of SIIDs on mobile interaction; however, the majority of the studies follow an ad-hoc approach and lack systematic investigation. This results in the inability of the research to draw a comparative judgement of the magnitude of the effects of different SIIDs on mobile interaction.

Furthermore, despite the established adverse effects of certain SIIDs (*e.g.*, cold ambience [231]), researchers have not proposed an adequate sensing mechanism to detect these SIIDs. The absence of such a sensing mechanism that detects the presence of SIIDs, results in the inability to further adapt the interface to accommodate these effects.

1.2 Contribution

1.2.1 Research Questions

Based on the research gaps identified above, we have identified three research questions addressed in this thesis:

- **RQ1. What are the effects of different SIIDs on mobile interaction?**
- **RQ2. How do these effects compare to each other?**
- **RQ3. How can mobile devices sense the onset of cold-induced SIIDs?**

The contributions of this thesis are three-fold and were explored via four different user studies presented in this thesis. First, we contribute to and consolidate the knowledge in understanding the effects of underexplored SIIDs on mobile interaction, namely ambient noise, stress, and dim ambient light, by conducting a systematic investigation. These SIIDs are commonly present in users' everyday settings and have recently been established as important SIIDs that lack investigation [235]. Understanding the effects of underexplored SIIDs enables creation of sensing, modelling, and adapting mechanisms to accommodate particular SIIDs avoiding misallocation of resources (*e.g.,* human, financial, technological).

Second, we provide a baseline comparison of these effects by employing a systematic methodology discussed in detail in Chapter 3. Namely, the study protocol presented in this thesis re-used the same observational, scoring, and calculation rules to measure user performance in three common mobile interaction tasks: target acquisition, visual search, and text entry that were re-used across multiple user studies (Chapters 4, 5, 6). This methodology could be used by other researchers to investigate the effects of underexplored SIIDs that were not studied within the scope of this thesis. Finally, we propose a sensing mechanism to detect the onset of one type of SIIDs – cold-induced SIIDs – using smartphone's built-in battery sensor, and demonstrate how off-the-shelf smartphone can be used to achieve this goal.

1.2.2 Author's Role and Contribution

Four publications are included as main contributions in this thesis presented in Chapters 4, 5, 6, and 8. These articles are published in prestigious, international and peer-reviewed conferences/journals in the field of Ubiquitous Computing and Human-Computer Interaction [233, 234, 236, 237].

I would like to clarify my contribution in the presented work. I was the lead author for the above-mentioned publications and performed the majority of the work (more than 50%). Precisely, I introduced the ideas behind the work, initiated the process, prepared the experimental designs, and handled the ethical bureaucracy, software development, participant recruitment, and data analysis. Moreover, I prepared the articles for submission and managed the revision process after receiving peer-review feedback. My co-authors provided me with feedback and suggestions on the design of the studies and data analysis techniques. Furthermore, my co-authors contributed to the write-up of the publications. To reflect this contribution and show appreciation to my co-authors, the scientific term "we" is used throughout the main chapters of this thesis.

1.3 Thesis Outline

This thesis is organised as follows. Chapter 2 provides an overview of related work conducted in this research area.

Chapter 3 outlines the methodology followed throughout the studies presented in this thesis. This chapter provides the motivation behind the methodological decisions used for data collection and data analysis as well as highlights the limitations of the employed methodological approach.

Chapters 4, 5, 6 present original articles focused on quantifying the effects of ambient noise-, stress-, and ambient light-induces SIIDs on common smartphone tasks performed during mobile interaction: target acquisition, visual search, and text entry.

Chapter 7 contrasts the effects of the SIIDs presented in Chapters 4, 5, and 6 on mobile interaction. This chapter draws conclusions based on this comparison and discusses the applicability and importance of this knowledge.

Chapter 8 presents a sensing mechanism to detect cold-induced SIIDs. This chapter suggests using smartphone battery temperature as a gauge to infer user's finger temperature when user is exposed to cold environments. Hence, smartphone's built-in battery temperature can be used to detect cold-induced SIIDs.

Chapter 9 discusses the contributions presented in this thesis in relation to existing research. It also outlines the limitations of the work presented in this thesis and summarises future research directions on SIIDs with suggestions. Chapter 10 provides final remarks and concludes this thesis.

Chapter 2

Background

This chapter provides a review of background work of research conducted in the area of Accessibility and SIIDs with a focus on mobile devices.

2.1 Accessibility of Mobile Devices

Mobile devices play an important role in people's everyday life [112]. Smartphones and other personal devices are prevalently used for communication purposes, to access information on-the-go, to perform work-related activities, and to stay in touch with family and friends via social media [135–137, 199, 247]. Mobile devices have expanded the capabilities of users, in particular by providing them with increased independence and freedom in their daily lives [54].

Despite the fact that mobile devices have also been used to assist people with special needs [54, 112, 152], off-the-shelf smartphones might often not be accessible to people with permanent impairments (*e.g.,* motor and visual impairments in particular) due to several design constraints (*e.g.,* including inability to access the content of the screen, small buttons, limited user input methods among others) [112]. Although these accessibility problems have been established and acknowledged [152, 266], off-the-shelf smartphones are still being primarily designed for able-bodied users without sufficient consideration of the wide breadth of accessibility issues [112].

Kane and colleagues suggest that extending the accessibility features of smartphones should be highly prioritised [112, 172, 245], particularly because people with disabilities use mass-market devices to avoid the social stigma [200, 244] as well as because there will always be a need for assistive technology as individuals with severe disabilities will require assistance either from the technology or a human [172]. Shinohara *et al.* argue that we, as a society, might be able to alleviate social misperceptions of disability by making mainstream technology more accessible [244]. Moreover, Wobbrock argues that the experience of disability in mobile interaction applies to us all to some extent [270], because our abilities are not static and change according to the context [179]. This also includes but is not limited to the effects of SIIDs on both able-bodied and permanently-impaired users. Therefore, the systems should be created to fit the abilities of the users and should follow adaptable and universal design strategies [75, 274].

Adaptable design implies including modifications to a standard design with the purpose of making the design usable according to individual's needs. Universal design sometimes employs adaptable strategies, meaning that the universal design can be adaptable, but should always be accessible [172]. The goal of accessible computing is to improve independence, access, and quality of life for people with disabilities [274]. However, this goal can be expanded to also improve user experience for able-bodied people who are temporarily impaired due to SIIDs [270].

In this section we focus on visual, motor, hearing, and cognitive impairments as they are commonly present among general population and have been extensively investigated in the context of mobile interaction. Furthermore, these four permanent impairments can be mapped to commonly acknowledged situational impairments in terms of their effects on mobile interaction. For example, the effects of permanent visual impairments can be similar to the effects of bright or dim light on mobile interaction, while the effects of cognitive impairments on mobile interaction can to some extent resemble the effects of stress. Similarly, the effects of motor impairments on mobile interaction might be similar to the effects of cold-induced SIIDs, as well as the effects of hearing impairments can be similar to the effects of ambient noise in mobile interaction [268]. Therefore, solutions suggested for accommodating the effects of permanent impairments can be used to address the effects of SIIDs to benefit the users of all abilities.

2.1.1 Visual Impairments

Visual impairments are widely prevalent around the world with a total number of 2.2 billion people suffering from this condition [195]. In the United States alone the number of visually impaired people exceeds 8 million [4]. As smartphones are everyday ubiquitous devices, they are widely used among visually impaired or blind users [188, 266]. Nevertheless, the accessibility of conventional mobile devices for visually-impaired users is restricted [86, 112]. For example, Li *et al.* found that visually-impaired users often need to have access to the information (*e.g.,* calendar and contact information) during phone calls and find it problematic as mobile phones have limited accessibility to accommodate this need [133].

In order to increase the accessibility of current mobile devices for visually-impaired users, literature suggests several methods that include the creation of novel interaction techniques and integration of novel technology to the existing devices [86, 112]. Nonetheless, Brady *et al.* in their study demonstrate that even though visually-impaired participants were, in most cases, willing to experiment with novel technology, they tend to quit and stop using the technology if their user experience was poor [27]. This example demonstrates that the usability plays a key role in adoption of the assistive technology [27].

Furthermore, Abdolrahmani and colleagues note that the experience of visually-impaired mobile users might be worsened by SIIDs due to cognitive load, as their attention will need to be divided in performing parallel tasks: between swiping the cane and interacting with the mobile device [1]. Leonard *et al.* argue that mobile phones can improve user experience of visually-impaired users in way-finding, memory recall and communication, but only if the effects of context and visual ability are adequately accounted for [131]. Therefore, it is important to account for situationally-induced impairments and disabilities when designing technology to assist visually impaired users [270].

Visually-impaired users encounter several challenges when using their mobile devices, including but not limited to accessing the content of the screen, inputting information on the devices (*e.g.,* text), protecting their input, and navigation [112]. To solve the aforementioned issues, researchers have suggested using voice [94, 194] and gesture [40, 111] modalities to interact with the device. Furthermore, a fair amount of research suggested several text entry techniques to improve the user experience in a text entry task [15, 25].

Moreover, researchers also considered solving the problem of privacy protection for visually-impaired users during mobile interaction [4, 14]. Finally, researchers also provided solutions on mobile devices for navigation and wayfinding problems to support visually-impaired users [12, 228]. The following sections summarise the existing literature in terms of voice-based interaction, gesture-based interaction, and existing text entry, privacy and security, and navigation solutions to support visually-impaired mobile device users.

Voice Interaction

One of the primary issues encountered by visually-impaired mobile device users is accessing the content of their screen [112]. Currently, the most common way for visually-impaired users to read the content of their screens is by using mobile screen reader. The use of these devices has undergone a significant growth in the past few years [63] even though voice interfaces were proposed as a solution to this issue back in the late 80s [94]. For example, Hill and Grieb developed "Touch 'n Talk" interface to assist visually-impaired users to perform computer-based tasks [94]. The authors show that "Touch 'n Talk" was well accepted by visually-impaired users and improved their performance in editing tasks and accessing menus as compared to key-based talking terminals [94]. Furthermore, O'Neill *et al.* developed a system with gestural input and voice output [194]. The researchers demonstrate that interacting with the computers without GUIs is possible and quicker than interacting with visual interfaces.

Pirhonen and colleagues took this approach one step further and implemented it on mobile devices [214] as an interface for a mobile music player – "TouchPlayer". The authors show that the usability performance of their participants significantly improved when using gesture and audio based interfaces when compared to a visual interface [214]. Similarly, Zhao *et al.* proposed "Earpod" – a system for mobile devices enabling eyes-free menu selection using touch input with a synchronously linked audio feedback [282]. Their results also demonstrate the feasibility of the system for non-visual interaction with mobile devices. The system was comparable to an iPod-like visual menu in selection accuracy; however, was slower in terms of efficiency. Nevertheless, the authors argue that this issue is solved by providing the users with extensive training [282].

In addition, text-to-speech is considered to be a popular interaction method for visually-impaired users to interact with their devices [110, 176]. For example, Sánchez and Aguayo presented a mobile messenger for the blind users [227]. The authors used a custom-built keyboard for input and integrated text-to-speech functionality for output in the messenger. Their results show that visually-impaired participants were satisfied with system and easily adapted to the input and output modalities of the messenger [227]. However, using text-to-speech functionality for these purposes has several potential issues that currently remain unresolved. For example, the users themselves do not feel comfortable to use voice interaction with the device to avoid attracting attention, and other social and safety reasons [245]. In addition, the presence of ambient noise causes difficulties to use a talking device for visually impaired participants [112].

Gestures

Another issue that has been acknowledged for visually-impaired or blind users is the usage of touch screen to interact with the device, as touch screens might constrain the device's accessibility [111]. The limitations of smartphones include but are not limited to restricted input, small screen size, and non-intuitive interfaces [247]. As a result, early work in this area suggested to provide feedback for touch screen interaction [40]. In particular, it was suggested that the accessibility of touch screens can be enhanced by providing haptic feedback [259] or by creating new non-visual interaction techniques [111] including eyes-free interaction and gestures [214]. Moreover, Pirhonen *et al.* suggest that the gestures should be reliable to be performed on-the-go to avoid interaction by mistake [214].

For instance, Kane and colleagues developed "Slide Rule" – a non-visual interaction technique to provide access for blind and visually-impaired users to a custom-developed phone book, email client, and media player [111]. "Slide Rule" utilises gesture interaction to achieve goals. Their results demonstrate that visually-impaired users completed the tasks significantly faster when using "Slide Rule" compared to when using button-based mobile screen reader. Furthermore, Azenkot and colleagues introduced "DigiTaps" – an eyes-free interaction technique with minimal audio feedback that enables visually-impaired users to interact with their mobile devices with little to no auditory attention [11]. This technique enabled blind participants to use gestures to input numbers on a smartphone at a relatively high entry rate and accuracy [11].

In addition, Ruamviboonsuk and colleagues presented "Tapulator" – a non-visual calculator to support visually-impaired users [223]. The system uses gestures instead of buttons and was universally designed to support any user who requires non-visual interaction with a calculator. In their preliminary evaluation, the authors show that the error rate was lower when using "Tapulator" as compared to a standard calculator application. Hence, the authors demonstrate that "Tapulator" can benefit blind and low-vision users in terms of speed and accuracy when compared to a traditional calculator application installed on smartphones [223].

Previous work has also suggested using devices' built-in sensors and user's spatial information to enhance the accessibility of mobile devices [132]. For example, Li *et al.* introduced "Virtual Shelves" – an interaction technique used to improve the user experience of visually-impaired users during mobile interaction [132]. The technique uses *proprioception*, the sense of position and orientation of one's body parts with respect to each other, and spatial memory for interaction [132]. The authors utilised the 3-axis accelerometer and the 3-axis gyroscope of a smartphone to determine the orientation and movement of the device for completing selection tasks and found that participants were correct in 81.8% of these tasks. Furthermore, the authors introduced shortcuts for the participants to be used for calling contacts, location-based tasks, email and weather checking tasks. They demonstrate that 88.3% of shortcuts were launched correctly. This work demonstrates how proprioception can be used to improve accessibility of mobile devices for the visually-impaired [132].

Furthermore, Ye *et al.* suggested using wearables to extend mobile interaction for visually-impaired users [278]. In their study the authors found that visually-impaired participants positively accepted the use of a wristband and a ring sensor to enable eyes-free interaction. The authors also suggest utilising a greater variety of tactile feedback to extend the interaction technique [278].

Similarly, Amar and colleagues implemented "ADVICE" – a handheld device that utilises a combination of tactile and audio feedback to assist visually-impaired users [6]. Their results demonstrate that the visually-impaired participants desire to use devices with the same functionality as their sighted peers [6]. Therefore, it is important to provide accessibility of commonly used mobile device's features. One such example could be photography, especially as earlier work has revealed that visually-impaired users found assistive photography for blind appealing and useful [260]. Therefore, several researchers developed assistive applications to support non-visual photography [3, 88, 103, 260]. Adams and colleagues investigated the requirements for building an application to assist blind photography and found that visually-impaired users had difficulties to operate with traditional smartphone camera applications [3]. As a result, the authors implemented a set of gestures that acted as shortcuts to operate with the picture taking application to reduce the complexity of operation. Moreover, visually-impaired users complained that it was challenging to identify context of the images (*e.g.,* time, place, date); hence the application had to save the metadata when the picture was captured together with the ambient audio and voice memo that can be recorded by the user [3].

In addition, Jayant and colleagues introduced "EasySnaps" – a photography application assisting visually impaired that provides an audio feedback [103]. The authors show that audio feedback improved the quality of photographs. These studies helped to identify requirements for creating photo-taking applications for visually impaired users and opens opportunities for design guidelines to support such applications for visually-impaired users.

Text Entry

Text entry is another challenging task for visually-impaired users to perform on a mobile device [41, 112]. Therefore, a significant amount of research has been conducted to improve text entry for visually impaired users [13, 15, 25]. For example, Bonner and colleagues present "No-Look Notes" – an eyes-free text entry system with a gesture-based multitouch input and a voice output [25]. The system arranges the characters on an 8-segment pie menu on the screen, and when the user touches each segment, the system announces the characters audibly in that segment. The user can select a desired character by dropping their second finger on the screen. The results of the system evaluation demonstrate that the user error rate was significantly lower when using "No-Look Notes" as compared to the VoiceOver technique; however, the text entry rate was lower when using "No-Look Notes" when compared to the VoiceOver technique [25].

Furthermore, Azenkot and colleagues present "Perkinput" – touchscreen text entry technique that uses multipoint touches, where each finger touch is represented as a bit [15]. The evaluation of this technique showed that blind users were faster and more accurate when using "Perkinput" for text entry as compared to Apple's voiceover [15].

In another approach, several research projects were based on integrating Braille technique for text entry to support blind participants due to their familiarity with the technique [80]. For example, Frey *et al.* present "BrailleTouch" – eyes-free text entry application for mobile devices to assist visually-impaired users [64]. The application has 6 buttons in total and allows multitouch input using both hands. Each alphabet letter is mapped to a combination of soft buttons pressed according to the Braille alphabet. The evaluation of the system showed that BrailleTouch had a potential to be used as an input technique for touchscreen devices [64]. Mascetti *et al.* also used the Braille alphabet for touch input on touchscreen devices [156]. However, unlike Frey *et al.* [64], the authors utilised gestures instead of pressing the buttons on the screen.

Futhermore, Oliveira *et al.* also used the Braille alphabet as a base for their system – "BrailleType" – to support text entry for visually-impaired smartphone users [193]. Unlike the work presented previously [25, 64], "BrailleType" does not support multitouch gestures and favours single touch gestures. The authors evaluated performance of "BrailleType" in comparison with Apple's VoiceOver system and demonstrated that although participants were slower using the system, they were significantly less error prone. Their findings suggest that "BrailleType" had a smoother adaptation than other complex methods [193].

In addition, Oliveira *et al.* in their follow-up study evaluated four different types of non-visual text entry methods – "QWERTY", "NavTouch", "MultiTap", and "BrailleType" – with blind participants [192]. The "QWERTY" method consisted of the traditional computer keyboard in tandem with a screen reading software. The "NavTouch" method was based on gestures navigating alphabet horizontally and allowing users to perform gestures on any part of the screen. The "MultiTap" keyboard was based on the keypad-based device. Finally, "BrailleType" was based on the Braille alphabet with audio feedback. The results of their study show that the efficiency of each method depends on the user's individual abilities. In particular, the authors reveal that users' spatial abilities, pressure sensitivity, and verbal IQ levels determine users' performance and can be used to determine the most suitable method for each particular user [192].

Privacy and Security

Another challenge that visually-impaired users face while interacting with their smartphones is privacy and security [4]. While sighted people are able to monitor the surrounding context and able to protect their vulnerable information during mobile interaction in public, visually-impaired users do not have such a privilege [4]. Azenkot *et al.* report in their work that visually-impaired mobile users were not even remotely aware of security and privacy threats during their interaction with smartphones [14].

To tackle this issue, Li *et al.* built "BlindSight" – an application for visually-impaired users to perform phone calls [133]. Unlike traditional visual in-call interface, "BlindSight" allows interaction with the keyboard and responds to auditory feedback. The authors report general preference of the visually impaired users for the application over traditional smartphone interface [133].

Navigation and Wayfinding

Navigation and way-finding are acknowledged as major issues that visually-impaired users experience [112]. For example, Kane *et al.* demonstrated that blind participants would use their smartphones while walking only if they are in a familiar area [112]. As a result, great deal of research projects have focused on improving navigation and way-finding experience of visually-impaired users with the help of a smartphone.

Hence, to assist visually-impaired users in wayfinding, Azenkot *et al.* present smartphone feedback methods "Wand", "ScreenEdge", and "Pattern" [12]. The authors used haptic feedback to give routing instructions to blind users on a predefined path. The "Wand" technique implied using the smartphone as a wand, and when the top of the phone pointed in the correct direction, the phone would vibrate. The device's built-in compass was used to determine the top of the device. The "ScreenEdge" entailed touching the edges of the device, and when the user touched the correct edge, the device would vibrate. The "Pattern" technique used the pattern of vibration pulses to indicate the correct direction. The evaluation of these techniques showed that the three methods were viable to give wayfinding instructions without demanding user's auditory attention and opens opportunities for creating new interaction techniques to support visually-impaired users [12].

Finally, Narasimhan and colleagues presented a system to enhance independence of blind smartphone users while travelling, but used text-to-speech modality to provide information to the users [176]. In addition, Sánches and Maureira have developed a system for mobile devices to navigate in the subway [228]. The program allowed users to plan the trip beforehand and the participants found it useful. Furthermore, the researchers demonstrated that the system provided the participants with an increased independence of movement in the subway network [228].

2.1.2 Motor Impairments

Musculoskeletal disorders of upper limbs are a common ailment that is the leading cause of disability [169]. The disorder includes but is not limited to such diseases as essential tremor and arthritis. The disorder is prevalent around the world with 7 million people in the US suffering from essential tremors [142], whereas, for example, in Australia every fifth person (age over 65) suffers from this condition [202]. The prevalence of arthritis has grown by 75% from 1990 to 2013 [30], and currently 15% of the Australian population suffers from arthritis according to Australian Bureau of Statistics [191]. As the interaction with mobile devices is prevalently designed to use hands, people who are diagnosed with musculoskeletal disorders of upper limbs and other motor impairments, experience difficulties when using their smartphones. For example, prior research has shown that upper limbs disorders are associated with missed targets, longer interaction times, lower text entry performance, which then lead to frustration and stress [119, 215, 275].

Research on designing and building assistive technology for motor-impaired has risen significantly in the past decades. Assistive technology started with a focus to improve usability experience when interacting with PCs including but not limited to input techniques [118, 119], text entry techniques [181], and one-handed keyboards [148]. For example, Myers *et al.* presented a software that allowed motor-impaired people to use handheld device as a substitute for a keyboard and a mouse for interacting with a computer [174]. The authors report that their system was well accepted by the motor impaired users and was considered to be less tiring as compared to the conventional keyboard and a mouse combination [174].

In another example, Trewin *et al.* show in their work that users with Parkinson disease require more time when completing target selection tasks on a stationary desktop, as well as they produce more errors compared to their able-bodies peers [257].

Nevertheless, the creation of touch devices and interfaces have benefited motor-impaired participants significantly, as touch screens do not require their users to have physical strength and/or dexterity that are needed to press physical buttons [82,174]. However, the location on the screen should be taken into account when designing technology for motor-impaired users, as they prefer selecting targets located in the center of the screen as it is easier and less error prone [203, 206]. For example, Guerreiro and colleagues investigated how tetraplegic users perform taps on a touch screen [83]. The authors found that the target size of 12mm was the most suitable for selection by motor-impaired users. The authors also found that the location of the target on the screen as well as the edge of the device had a significant effect on the performance of tetraplegic users. The researchers advice using these details when designing assistive technology for motor-impaired users [83].

In a follow-up study, Guerreiro *et al.* evaluated the most common interaction techniques – “Tapping”, “Crossing targets”, “Exiting”, and “Directional Gestures” – with motor-impaired users [82]. The findings of their study suggest that although accuracy and precision depended on target size, overall “Tapping” was found to be most effective and preferred amongst participants with tetraplegia [82]. Moreover, Nicolau *et al.* extended this work by comparing the performance of both able-bodied and motor-impaired users on the aforementioned techniques, and show that “Tapping” and “Crossing” can be performed by both able-bodied and motor-impaired groups of users; however, the latter would have a higher error rate [187]. Nevertheless, “Directional gestures” have been shown to be suitable for able-bodied users, but completely inadequate for motor-impaired users. The authors also mention that the target size and position on the screen had an effect on performance of both user groups [187] as well as the posture when holding the device [188].

Similarly, Froelich and colleagues proposed “Barrier Pointing” – a system that uses a mobile device screen’s edges and corners to provide greater stability for motor-impaired users in order to improve their accuracy [65]. The authors evaluated their system with motor-impaired participants and found that “Barrier Pointing” technique improved performance of motor impaired participants in target acquisition tasks. Furthermore, the authors suggest integrating haptic feedback into the system to further improve the performance of motor-impaired users in target selection tasks [65].

Text input on mobile devices are considered to be challenging for motor-impaired users. Therefore, there was a need to create alternative text entry techniques to enhance the accessibility of mobile devices. For example, Wobbrock and colleagues introduced "Edgewrite" – an alternative text entry method with a custom alphabet that uses unistrokes [275]. The authors have demonstrated the method's usability efficiency and effectiveness on users with motor disabilities and able-bodied users. This work then was extended to use pressure strokes entered via an isometric joystick [271]. The authors showed that this method was a comparable alternative to the existing text input techniques, empowering users to utilise it while eyes-free without a significant effect on text entry performance [271].

Furthermore, Kane and colleagues presented "TrueKeys" – a system presented as a keyboard layout that models the word frequency and error patterns to automatically correct typing errors [113]. "TrueKeys" was developed to support and improve performance of motor-impaired users in text entry tasks. The authors showed that "TrueKeys" significantly reduced error rates for both motor-impaired and non-impaired users. The authors also suggest using personalisation algorithms to improve text entry performance as they observed consistency in typing errors within individual participants [113].

Finally, bio-signals could be used to enhance the interaction with mobile devices for motor impaired users. For instance, Guerreiro and Jorge suggest using an electromyographic signals to control mobile devices in order to assist individuals with spinal cord injuries [81].

2.1.3 Hearing Impairments

Interaction with the mobile device can be challenging for users with hearing impairments (Deaf or Hard of Hearing – *DHH*) due to different factors. For instance, Glasser and colleagues show in their work that Deaf or Hard of Hearing users have challenges when using speech-controlled user interfaces [68] due to the fact that automatic speech recognition systems are commonly trained on the speech produced by hearing users [62]. The authors suggest that speech-controlled systems should be able to give a better feedback to DHH users to improve the usability. For example, it would be ideal if the system asked the user to repeat a specific word rather than a whole phrase. The researchers also show that having a visual feedback for speech-controlled systems enhances their accessibility features [68].

Himmelsbach *et al.* show in their work that hearing-impaired users prefer touch interactions when using their mobile devices [96]. Moreover Pfeuffer *et al.* suggest extending mobile interaction by adding gaze and demonstrate that gaze complements touch and, hence, is applicable when vocal interaction is not appropriate [207]. The authors use gaze as an extension and a replacement of direct touch. Therefore, gaze can be used by DHH users in cases when hands-free interaction needs to be performed [207].

Moreover, Hong and colleagues demonstrate that the accessibility of video content (including the content played on mobile devices) can be extended by providing "Dynamic Captioning", an approach that enables mapping captions to character faces and then placing the captions in a non-intrusive area around the face [100]. The authors demonstrate that their approach was effective and well received by the hearing-impaired participants [100]. Similarly, Avvenuti and Vecchio extended the accessibility of mobile devices by presenting an interpreter to convert the interaction between the user and the application from vocal to visual [10]. In particular, their system transforms vocal dialogues into a sequence of visual screens [10].

Morever, Massaro *et al.* presented an iOS application used to supplement speechreading by displaying an animated face to the user and transforming speech into visual cues [158]. In addition, Sun *et al.* presented "Lip-Interact" – a mobile interaction technique using silent commands [253]. The authors initially designed the technique to allow hands-free interaction similar to voice interaction; however, unlike voice interaction "Lip-Interact" accounts for privacy and social norms. As the technique allows lip interaction with the mobile device, its usability could assist not only those requiring hands-free interaction but also hearing-impaired users especially given the efficiency of the technique that the authors demonstrate through the user study [253].

Nasser and colleagues suggest extending the interaction with mobile devices by adding a wearable device to enhance the usability of mobile devices [177]. In particular, the authors suggest providing a thermal feedback through the wearable device to provide feedback to DHH users. The authors demonstrate that the thermal haptic feedback has a potential of being well accepted among the users, as they were successful in differentiating between different feedback cues [177].

Finally, mobile interaction becomes even more challenging when a combination of impairments persists. For such users, Azenkot *et al.* developed “GoBraille” – an Android application built on a novel framework (named “MoBraille”) that provides information on bus arrival times as well as information on bus stop landmarks [13]. This software allowed deaf-blind users to travel more independently and safely [13].

2.1.4 Cognitive Impairments

Cognitive impairments usually imply having difficulties in processing information that requires attention, thinking, and memory [89]. Cognitively-impaired users with attention disorders find it challenging to manage parallel tasks [180]. Therefore, users with cognitive impairments might find it difficult to type messages, as the soft keyboards require an increased focus-of-attention as the users need to look at the buttons while typing [275]. Hence, as Himmelsbach and colleagues mention in their work, ease of use is the main factor for cognitively-impaired participants when using their mobile device [96].

Dawe presented requirements for mobile devices to enhance their accessibility for cognitively-impaired users [55]. The author’s findings include such requirements as simplified navigation menu, or a rugged handset. The author also demonstrates the need for remote communication using mobile devices, *e.g.,* through voicemails, and the need for supporting safety check-ins with a key aspect of tracking each other [55].

Another significant problem for cognitively-impaired people is to navigate in the environment [79]. As the risks of being lost are quite high, people with cognitive-impairments depend on their caregivers when going out or finding their way [79]. For this reason, assistive mobile technology has focused largely on creating applications to support navigation for cognitively impaired users. Chang and colleagues present a wayfinding system that provides support to cognitively-impaired users by providing context triggered prompts [47]. The main idea of this wayfinding system is to tag the context with the QR codes and provide end-user specific response. The authors show that the system was friendly and reliable in providing wayfinding responses to the participants. The researchers suggest that their method can be extended to be used with RFID tags and bluetooth beacons [47].

Similarly, Poppinga and colleagues implemented "NavMem Explorer" – a system to support users with mild cognitive impairments to navigate within the environment [216]. The authors' system was efficient in wayfinding tasks and, hence, it can potentially support independence and social life of the users with mild cognitive impairments by allowing them to go out alone [216]. In addition, Liu and colleagues developed another system to support navigation and wayfinding tasks of cognitively impaired individuals [138]. The system provided different feedback modalities including images, audio, and text for users. The authors found that the choice of a modality was purely individualistic and depended on users' personal preference. In addition, authors also found that feedback should be provided to users at appropriate times to improve their user experience [138]. Finally, Chang and Wang in their research show that when creating wayfinding technology for cognitively-impaired users, it is beneficial to support the technology with video modality as participants perform wayfinding tasks better [48].

2.2 Situationally-Induced Impairments and Disabilities

The aforementioned permanent impairments can be mapped to situational impairments as the effects of both permanent and situational impairments might somewhat be similar, albeit to a lesser extent [268]. Situational visual impairments can be caused by bright or dim ambient light [255]; situational motor impairments can be caused by walking or cold hands [70,268]; situational hearing impairments can be caused by ambient noise, and situational cognitive impairments can be caused by stress or any other type of cognitive load [268].

A decade ago, Wobbrock anticipated the similarity of the effects of permanent impairments and SIIDs on mobile interaction [268] which has then been demonstrated in research [279]; hence, it is important to account for SIIDs when designing technology in order for it to be accessible. Prior research has shown that users consider the cost of situational context, when addressing their needs using smartphones [247]. Due to the contextual restrictions, user's information needs are delayed to be addressed later or forgotten [247]. Furthermore, people create challenging situational contexts by trying to multitask as their attention is divided between the active task and the task to address their informational need [247].

Mobile devices are as small as the palm of a hand and are used in a number of dynamic environments [71]. These factors can lead to SIIDs (also known as situational impairments) [242], which can pose significant challenges to effective interaction because our current mobile devices do not have much awareness of our environments, and thus cannot adapt to them [71]. Sohn *et al.* show in their study that 40% of the time, participants used smartphone browsing to address their information needs [247]. Moreover, 72% of their information needs were prompted by contextual factors (*e.g.,* location, activity, time, conversation) [247].

Furthermore, it is important to consider SIIDs when permanently-impaired users are interacting with their mobile devices, as they aggravate the effects of permanent impairments. For example, very bright or dim lighting can cause accessibility issues for users with low vision [112]; mobility worsens mobile interaction performance for motor-impaired [175]. Therefore, creating situationally aware mobile devices for overcoming situational impairments and disabilities will benefit the users of all abilities [270].

This section provides and overview of research on SIIDs in terms of *Understanding* their effects on mobile interaction, *Sensing* SIIDs and building detection mechanisms, *Modelling* SIIDs or user behaviour, and mobile interaction under SIIDs, and *Adapting* the interface to accommodate the effects of SIIDs [273]. Further, it summarises the design guidelines suggested by various researchers in the field.

2.2.1 Understanding

Understanding SIIDs is an essential step in conducting research in the field of SIIDs as it plays an important role to accumulate and build knowledge on the effects of SIIDs on mobile interaction. It is also an important step as it enables conducting future research on SIIDs in terms of building sensing, modelling and adapting mechanisms to accommodate SIIDs and reduce their effect on mobile interaction. As a result, this can lead to the creation of situationally aware ubiquitous mobile devices that enhance user experience [270].

A great deal of research was conducted on understanding the effects of various situational impairments on mobile interaction; however, most of the work follows an ad-hoc approach (different studies used different smartphone tasks and measure variables without following a consistent protocol) and lacks systematic investigation. Moreover, some SIIDs received more attention than others within our research community. For example, walking has been widely investigated, while the effects of ambient noise remained underexplored [235]. This section summarises the literature in terms of understanding the effects of walking, encumbrance, cold ambience, ambient light, and divided attention on mobile interaction.

The Effects of Walking on Mobile Interaction

Kane *et al.* investigate the effects of walking on mobile interaction performance when using soft buttons of varying sizes [115]. The participants of the study were asked to scroll through the playlist to find a given song and tap on the song to play it. The authors found a significant effect of button size and an interaction of button size and movement on participants' performance. Their findings show that the button size affects the task completion time and error rate, and its effect size depends on the movement [115].

In another example, Lin *et al.* investigated the effect of walking on tapping task performance [134]. The authors found that walking in the environment with obstacles had a negative effect on target selection accuracy, reduced the walking speed and increased the perceived workload [134]. MacKay and colleagues studied the effect of walking on scrolling techniques on a PDA using a stylus [149]. The authors demonstrated that the participants took significantly longer time to complete scrolling tasks when they were walking as compared to a static condition [149].

Schildbach and Rukzio also studied the effect of walking on selection tasks. They have additionally extended their study on understanding the effects of walking on reading performance as well [239]. The authors demonstrated that participants' error rate increased by 24% and target selection time increased by 31% when they were walking. Moreover, walking decreased their reading speed by 19% and increased cognitive load by 16%. Similarly, Mustonen and colleagues demonstrate that walking deteriorates visual performance in reading and visual search tasks [173]. In addition, Bergstrom-Lehtovirta *et al.* studied the tradeoff between the walking speed and target acquisition performance [23]. The authors found that 40-80% of the user's preferred walking speed enabled an optimal target acquisition performance [23].

As it is common to type on the smartphone while walking, researchers investigated the effects of walking on text input tasks. For example, Mizobuchi and colleagues studied the effect of walking on text entry [168]. Their work focused on understanding how this effect varied depending on different sizes of the text entry keys. The authors found that in general walking slowed down the text entry speed and increased the error rate; however, this speed increased with larger sizes of the keys while the error rate declined [168]. Similarly, Nicolau and Jorge in their work investigate the effects of walking on text input performance [188]. The authors demonstrate that walking led to more errors during text entry; however, this effect could be somewhat compensated by increasing the target sizes. The authors suggest using predictive text entry methods, correction algorithms, and/or adaptive keyboards to eliminate the negative effect of mobility on text entry. Moreover, the authors suggest that text entry methods should be able to sense the mobility or any other hand-tremor and then adapt the interface accordingly by increasing the target sizes in order to enhance user performance [188].

Harvey and Pointon further studied the effects of walking on mobile search tasks [90]. The researchers hypothesise that walking causes attention distraction during mobile interaction and, hence, negatively affects mobile search performance. They conducted a study with 19 participants in a controlled laboratory settings and asked their participants to complete search tasks in three conditions: being seated, walking on a treadmill, and walking with obstacles. The results of their study show that the participants found it to be more difficult to complete search tasks when walking on a treadmill and with obstacles as compared to a seated condition [90].

The Effects of Encumbrance on Mobile Interaction

As it is common to be interacting with the mobile device while at the same time being encumbered (*e.g.,* carrying shopping bags), Ng and colleagues investigated the effect of encumbrance on mobile interaction [182]. The results of their study show that encumbrance has a significant negative effect on accuracy of target selection tasks with participants having more errors when they were carrying a small and a medium bag, as well as a thin and a thick box. Furthermore, the authors added the effect of mobility to the encumbrance by instructing participants to walk according to a defined path while being encumbered to complete target selection tasks on a smartphone. The researchers found a significant negative interaction effect of encumbrance and mobility on mobile interaction performance. Furthermore, the authors found a negative effect of encumbrance on the walking speed with a decline of approximately 41% as compared to a static position [182].

In their follow-up work, Ng *et al.* extended this research by investigating the effects of encumbrance on different three interaction postures: two-handed mode using index finger to interact with the device, two-handed mode using both thumbs to interact with the device, and one-handed mode using a thumb to interact with the device [183]. The results of this study showed that accuracy in target acquisition tasks dropped to 48.1% in a one-handed interaction mode using index finger, while the error rate increased by 40% in one-handed interaction mode using thumb when participants were encumbered [183].

Investigating the effects of combined situational impairments is not common within the research community; however, Ng and colleagues studied the effects of both encumbrance and walking on touch-based gestures: tapping, dragging, spreading and pinching, and rotating [185]. The authors used Fitts' law measurements to quantify these effects on the above-mentioned gestures. The findings of the study showed that encumbrance and mobility had a negative effect on the performance of each gesture, except for rotational activity. In particular, the participants were less accurate when performing tapping, dragging, spreading and pinching gestures. In terms of task completion time, participants were slower when performing tapping, dragging and rotation tasks. The authors demonstrate that it is important to account for physically demanding contexts when designing interaction techniques for mobile devices [185].

The Effects of Cold Ambience on Mobile Interaction

Some research work focused on understanding the contextual and environmental factors that might lead to SIIDs on mobile interaction. For example, Choi investigate the effects of contextual changes on human behaviour during mobile interaction [51]. The author found a significant negative effect of walking on reading comprehension task on a mobile device as the reading time increased when the participants were walking as compared to a sitting condition. The author also found that under different lighting conditions reading comprehension performance was significantly different with a longer response time under the dark ambient light as compared to the bright ambient light condition [51].

Previous work investigated the effect of cold ambient temperature on mobile interaction from the perspectives of fine-motor movements and vigilance [231]. The findings show that cold ambience had a negative effect on fine-motor performance during mobile interaction on target acquisition tasks, but not vigilance. In particular, target acquisition time becomes longer and touch accuracy drops when participants are exposed to cold environment as compared to the warm environment [231].

Goncalves *et al.* extended the previously mentioned study [231] and investigated the effect of cold ambience on mobile interaction performance in target selection tasks [76]. The researchers show that under the cold ambience smartphone interaction performance deteriorates as the throughput drops and error rate increases. Based on these findings, the researchers suggest using ambient temperature as one of performance predictors in Fitts' Law [59].

The Effects of Ambient Light on Mobile Interaction

Another contextual factor that has been investigated on mobile interaction performance is ambient light. Lee and colleagues demonstrate in their study the effects of ambient light on visual search performance during reading [129]. The authors demonstrate that the search speed increased as the surrounding illuminance increased. This means that dark ambient light was associated with slow search speed, while bright ambient light improved the participants' performance in visual search tasks [129]. Furthermore, the authors also show that the size of characters in reading task had an effect on search performance of their participants: bigger characters were associated with higher search speed. The authors recommend the minimum size for character of 3.3 mm for optimal search performance on a mobile device [129].

Moreover, Liu *et al.* studied the effects of different illuminance levels on character detection task on a mobile device [139]. The researchers report that their participants' performance decreased when they completed the character detection task under bright illuminance as compared to low illuminance levels due to glare of the device [139].

The authors demonstrate the importance of accounting for ambient illuminance on mobile interaction particularly for the cases when mobile interaction comes at a cost (*e.g.,* during medical operation in need of using mobile device to control technology) [139].

The Effects of Divided Attention on Mobile Interaction

Finally, there was an attempt to study the effects of not only the external, but also "from within" factors on mobile interaction (*i.e.,* coming from user's internal states [273]). For instance, Oulasvirta and colleagues investigated the effect of fragmented attention caused by moving through urban settings on a mobile browsing task [196, 197]. The authors report that participants attention focused for 6-16 seconds on the task with the intermittent breaks of 4-8 seconds. The authors' results show that attention resource competition is real and constrains mobile interaction.

2.2.2 Sensing

Mobile device sensors have been widely used in the HCI and UbiComp communities for various purposes. For example, a fair amount of work focused on using device sensors to detect context (*e.g.,* [2, 56, 240]), while other researchers used smartphone sensors for activity recognition (*e.g.,* [8, 252, 265]). Similarly, smartphone sensors have been used to detect SIIDs and this section provides an overview of existing work in terms of sensing SIIDs.

For example, Goel and colleagues used smartphone's built-in accelerometer to detect if a user is walking [70]. Based on this sensing, the authors then adapted the keyboard to overcome the SIIDs caused by walking. In particular, the authors used the displacement and the acceleration of the device for the classification model for text entry. The authors demonstrate how successful detection of walking then can lead to creation of adapting interfaces to mitigate the effects of walking on a text entry [70].

Furthermore, smartphone sensors have been used to detect essential tremors [45, 67, 109, 225]. These works utilised smartphone's accelerometer sensor to detect hand tremors. For example, Daneault *et al.* used smartphones to collect and process the accelerometer data which they then used to correlate with the laboratory accelerometer data [53]. The authors found that the tremors with amplitudes lower than $1mm$ were not detected with the smartphone; however, for high amplitude tremors ($> 1mm$) the correlation between the smartphone data and the laboratory accelerometer data was relatively high ($r > 0.88$). These above examples use accelerometer to detect both SIIDs (*i.e.,* caused by walking) and permanent impairments (*i.e.,* essential tremor); hence a detection mechanism designed to sense SIIDs can be used to also detect permanent impairments as was envisioned by Wobbrock [268].

Azenkot and Zhai [16] found that majority of users at least "sometimes" used their phones with either the thumb of their dominant hand (one-handed holding posture), their dominant index finger (two-handed holding posture), or both thumbs (two-handed holding posture). Therefore, a substantial amount of work focused on identifying the grip and device holding posture of the users. For instance, Goel *et al.* in their work present "GripSense" – a system to detect hand-posture based on the device's gyroscope, vibration motor, user touch size, and swipe shape [72]. The authors demonstrate that their system was extremely accurate when detecting if the device was on the table or held in hands with a detection accuracy of 99.7%. However, this accuracy slightly dropped when detecting between different hand postures (84.3%). Furthermore, the authors suggest their system can be useful to detect when the user is situationally-impaired due to encumbrance and can only operate the mobile device in one-handed interaction mode [72].

Similarly, Gupta and colleagues also focused on identifying users' grip strength. The authors suggested using a concept of a virtual spring to detect the strength of the grasp when holding the device with one hand in order to enable eyes-free interaction [85]. In their work they presented an electro-mechanical system called "SqueezeBlock" that can be used in various use-case scenarios, *e.g.,* changing the ringer volume by squeezing the device [85]. This concept can be applicable for situations when the user is encumbered to ease the interaction with the device by limiting to the squeezing gesture.

This feature has then later been implemented within Google smartphones. Precisely, Google has implemented "Active Edge" feature on Pixel mobile devices to detect the grip force of the user. Depending on this grip force, the smartphone launches Google Assistant, thus allowing quick interaction for the user [218]. This feature can be applicable during situational impairments when the user cannot interact with the device with both hands or requires quick activation of the Google Assistant with one hand (*e.g.,* encumbrance, diverted attention). Quinn and colleagues from Google evaluated "Active Edge" and report that the technique was found to be easy, comfortable, and reliable as an interaction technique to silence the alarm, take pictures, and voice commands [218].

Several researchers proposed using smartphone's built-in sensors to protect privacy issues; hence, address privacy-induced SIIDs [87, 143]. For example, Haque *et al.* suggested using smartphone accelerometer sensors for authentication purposes [87]. In particular, the authors recommend using accelerometer to distinguish the user's gait pattern and, hence, authenticate the user. The authors claim that this approach can be extended to a conventional smartphone users to secure authentication in vulnerable locations and situations, *e.g.,* at a night time when unlock pattern can be visible due to the screen light of the device [87].

Moreover, Mariakakis *et al.* in their recent work presented "Drunk User Interfaces (DUI)" that are used to quantify the effects of alcohol on human motor coordination and cognition during mobile interaction [153]. They utilised sensor data in combination with user input data to build prediction models to detect blood alcohol levels. The authors demonstrated that their system was highly accurate to detect users' blood alcohol levels with an absolute mean error of $0.005\% \pm 0.007\%$ and with a strong Pearson's correlation of 0.96 with the ground-truth measurements.

Mobile device sensors have been suggested to be used to detect surrounding context. For example, Yi and colleagues utilised a single tri-axial accelerometer attached to a mobile device to sense contextual information and have shown that their system was able to successfully determine the mobile state of the user and ambient light [280].

Similarly, Mass and Madaus discuss using smartphone pressure sensors to detect environmental pressure [157]. The authors claim that the network of smartphones could provide a reliable pressure data as it would not be influenced by external factors [157]. In addition, Overeem and colleagues demonstrated in their work that smartphone temperature data can be used to predict daily average air temperature [198].

Finally, Reis and colleagues presented two context-aware prototypes that were able to automatically adjust volume depending on the contextual situation based on the detected level of ambient noise [221]. The interfaces used smartphone's microphone to sense the levels of surrounding noise.

The prototypes also allowed accounting for user preferences that were collected through users' settings and modifications. The authors demonstrate that the systems were positively accepted amongst the users, and hence show that accounting for noise-induced SIIDs is important when designing interaction technology [221].

We extend this literature by presenting a sensing mechanism to detect cold-induced SIIDs on mobile interaction and present our findings in Chapter 8 of this thesis.

2.2.3 Modelling

Modelling is an aspect of SIIDs research that focuses on modelling either environment or user behaviour to enhance our understanding of SIIDs. Furthermore, modelling can include creation of machine learning models that are used to predict either the effect of SIIDs on mobile interaction or human behaviour under SIIDs. In addition, several researchers have created models which were used for creation of adaptive user interfaces to accommodate the effects of SIIDs. This section summarises modelling examples in SIIDs that exist in literature and have been implemented by the researchers.

For example, Flatla and Gutwin developed and presented individual models for colour differentiation for users affected by permanent (colour vision deficiency) or situational visual impairments (*e.g.,* bright light) [60]. The authors demonstrate that their model was effective in detecting user's individualistic colour differentiation abilities and efficiently improved colour adaptation of mobile device's screen [60].

There was an element of modelling in the work by Mariakakis *et al.* when creating "Drunk User Interfaces" [153]. In particular, the authors developed an application that used machine learning models to determine the blood alcohol level of the user. The authors trained machine learning models on real human behaviour data observed and collected from interaction performance and sensor data [153].

Mott and Wobbrock presented "Cluster Touch" – a touch offset model to improve touch input accuracy for motor-impaired users. This work can be extended to support users experiencing SIIDs due to walking [171]. The general model for "Cluster Touch" is built based on touch data from multiple users and can then be personalised based on individualistic touch behaviour of the users. The authors demonstrate the efficiency of their technique, as "Cluster Touch" improved touch accuracy of motor-impaired users by 14.65%; while this number for situationally-impaired users reached 6.81% as compared to the native touch baseline. Furthermore, the touch accuracy during an offline analysis improved by 8.21% and 4.84% for permanently and situationally impaired users respectively [171].

In addition, several works have suggested using language models to adjust key press probabilities [5, 78, 84]. For example, Buschek and Alt presented "ProbUI" – probabilistic graphical user interface framework for mobile devices that defines touch behaviours, evaluates them probabilistically, and infers touch intentions based on the first two steps [35]. This framework could be used to improve the gesture and touch accuracy in situations resulting in a reduced touch accuracy due to the user being situationally-impaired (*e.g.,* walking).

As users perform differently when interacting with their mobile devices, it is necessary to take into account personalised characteristics of human behaviour in mobile interaction [269]. For instance, Buschek *et al.* emphasise the importance of individualistic characteristics of touch interaction [36]. The authors demonstrate that the touches performed using thumb are more individualistic than the index finger touches. Hence, the mobile devices should be able to differentiate between different holding postures and adapt accordingly depending on the interaction mode [36].

In addition, one of the examples of successful personalisation in text entry was the system named "Text Text Revolution" (TTR) presented by Rudchenko and colleagues [224]. In their user study, the authors trained target resizing on touch point collected from the participants first 10 rounds of performing tasks in TTR, and simulated personalised target resizing models in the second 10 rounds of TTR. Their results showed an improvement in text entry as the error rate reduced by 21.4% [224].

2.2.4 Adapting

The adapting aspect of SIIDs research is directed to create adaptive interfaces to accommodate the effects of different SIIDs. This section presents several adaptive interfaces existing in the literature, that are used to mitigate the effects of walking, encumbrance, situational visual impairments, and situational privacy issues that arise due to the vulnerability of the environment.

Interface Adaptations to Accommodate the Effects of Walking

As walking was paid more attention than other SIIDs within the research community, several researchers worked on creating adapting interfaces to accommodate the effect of walking on mobile interaction. For example, to mitigate the effect of walking on song selection task, Kane *et al.* created an adaptive *walking user interface* for a music player that scales target sizes based on user motion [115]. The interface shrinks the buttons when the user is standing still; however, when the user is walking, the targets and text expand in size to improve readability and touch access [115]. Their evaluation results show that the interface adaptation to accommodate walking significantly improved task completion time; however the authors suggest that task difficulty and other individual characteristics of the users should also be taken into account to create successful adaptive interfaces to mitigate the effect of walking [115].

Another suggestion to overcome walking-induced situational impairments was to use screen stabilisation techniques to stabilise the content of the screen [219]. For example, Rahmati *et al.* present "NoShake" – a system that utilised smartphone's accelerometer to detect if the device was shaking and then compensate for shaking by shifting the screen content in the opposite direction. The results of their study show that "NoShake" improved user experience in presense of shaking. The authors also suggest that the system could improve user experience of people who are unable to hold the device steadily, *e.g.,* those suffering from Parkinson's disease [219].

Yamabe and Takahashi also proposed a user interface adaptation approach to accommodate for the effects of walking in mobile interaction [276]. In particular, the authors suggest changing the size of the screen elements based on the display movement. Furthermore, the authors suggest taking into account user's individual characteristics when designing adaptive interfaces to diminish the effects of walking [276]. Brewster suggested accompanying small buttons with the sound feedback to enhance the usability of the interface [31] that might particularly be useful for situations when touch is inaccurate, *e.g.,* due to walking.

A fair amount of work has focused on creating adaptive interfaces to improve text entry methods as it is one of the common tasks users perform on their smartphones. For instance, Goel *et al.* introduced "WalkType" – an adaptive text entry system for smartphones that compensates for movement when users are walking [70]. The system utilises devices' accelerometer sensors to detect if the user is walking. The authors demonstrate that "WalkType" reduces errors by 45.2% and improved typing speed by 12.9% [70]. Similarly, Himberg and colleagues developed an adaptive keyboard that arranges keys according to the spatial distribution of keystrokes [95]. The results of their evaluation show that the changes in the keyboard are consistent within each user. Hence, the authors conclude that personalisation should be taken into account when designing adaptive keyboards [95].

In addition, Go and Endo introduced personalisation in adaptive keyboards by presenting "CATKey" – an adaptable keyboard for touchscreen devices with customisable functions [69]. The keyboard was able to adapt each key's centroid to the centroid of recorded keystroke points. Although "CATKey" did not have any significant advantage in terms of improved efficiency in typing during evaluation, the participants expressed their preference towards "CATKey" as compared to the traditional "QWERTY" keyboard [69]. This keyboard is another example how text entry can be improved during walking.

One-Handed Interaction to Overcome Encumbrance

Buschek and colleagues in their work presented and evaluated dynamic adaptations of mobile touch interfaces to overcome the inconvenience of using a large screen in a one-handed interaction mode [37]. The authors present three techniques – "Roll", "Bend", and "Move" – to locate GUI elements on the screen at a comfortable reach for the user. The authors show that their techniques improved users interaction due to the increased comfort of usability, decreased fatigue, and ease of grip [37]. These techniques could be used to overcome the effects of encumbrance during mobile interaction, as it is common to perform a single-handed interaction with the device when encumbered [185].

Karlson and colleagues introduced "AppLens" and "LaunchTile" – user interface techniques designed to enable one-handed interaction with the mobile device [117]. Both interfaces used the zoom technique with a difference that "AppLens" used a tabular fisheye, while "LaunchTile" used a pure zoom to be used with specific gestures to perform using a thumb [117]. The authors demonstrate that the users were more efficient when using "AppLens" as compared to "LaunchTile" in terms of task completion time and preferred using it over "LaunchTile".

Karlson and Bederson presented "ThumbSpace" – an interaction technique for one-handed interaction mode using thumb [116]. The results of their evaluation show that "ThumbSpace" was positively received by the users and improved their performance in completing target acquisition tasks on a smartphone designed for small size targets. Furthermore, the authors suggest this interaction technique could also be useful for encumbered users, as it allows to free one hand and effectively complete smartphone interaction [116].

"Twiddler" is a text-entry technique presented by Lyons and colleagues [148]. Similar to work mentioned above [37,116,117], this method could be used for text entry when a user is being encumbered as it enables single-handed text entry and proves to be effective and intuitive as the authors demonstrate in their work [148]. Another system that can be used in encumbered situations is "Unigesture" developed and presented by Sawazal *et al.* [238]. "Unigesture" – a tilt-to-write system that enables one-handed text entry [238]. "Unigesture" uses accelerometer data to determine the tilt of the device and acquire the input character that is mapped to a particular tilt. The evaluation of the system demonstrated that the individual characteristics of the user had a greater effect on their text entry performance. Hence, the authors suggest taking into account personal characteristics of users when designing adaptive technology for text entry [238].

In addition, Boring and colleagues created the "Fat Thumb" interaction technique that allows using thumb's contact size with a small size for panning and a big size for zooming [26]. After evaluating this technique, the authors demonstrate that the "Fat Thumb" interaction technique compared quite well with the existing mobile interaction techniques. "Fat Thumb" could be used efficiently in situations when the user is encumbered or cannot interact with the device in a traditional manner [26].

Furthermore, not only being encumbered can cause difficulties when interacting with a mobile device, but also small screen size [89, 279] can lead to the "Fat finger problem" [246]. Baudisch and Chu suggest using the back of the device to solve this problem during selection tasks on a mobile device [21]. The researchers show that using the back of device for mobile interaction enables higher accuracy and lower error rate in target selection tasks independent of device size [21].

Moreover, Buschek and colleagues also suggest using back of the device to allow rapid and efficient typing as it engages all ten fingers of the users [39]. The authors' technique [39] can be used to solve the problem of a small screen that is also stated to cause situational impairments to mobile device users [31, 279].

Finally, as research has shown that hand posture can either improve or deteriorate the performance on text entry, some work took into account the holding posture of the device in text entry [71]. For example, "ContextType", a system that infers users' hand postures to improve text entry on mobile touch screen devices. "ContextType" supports typing with four hand postures: two thumbs, just the left thumb, just the right thumb, and either index finger [71]. "ContextType" switches between underlying touch-models based on inference about how the user is holding the device while typing, without changing the visual layout of the keyboard and leverages previous work by Goel *et al.* on "GripSense" based on detecting holding posture for the device [72] that was mentioned earlier in this chapter [71].

Non-visual Interaction to Accommodate Situational Visual Impairments

In some situations it is important than the mobile device allows eyes-free interaction, *i.e.,* when the user cannot interact with the device due to *e.g.,* mobility, divided attention, or situational visual impairments. To address this requirement, Jain and Balakrishnan developed a bezel gesture-based text entry method to allow eyes-free text entry on a mobile device [102]. Their system was easy to adapt to, as the novice users transitioned to being an expert after one hour of training. The authors also demonstrate that the bezel-based text entry was comparable in terms of speed, accuracy, ease of learning and use with existing traditional text entry methods [102]. This example showcases how eyes-free text entry can be enabled using gestures.

Similarly, Chen and colleagues presented “Swipeboard” – an eyes-free text entry method that uses swipe gestures for inputting text [49]. The technique utilises two swipes: 1) to specify the region of the character location, and 2) to select the necessary character. The authors demonstrate that with an extensive training users perform text entry 15% faster using “Swipeboard” than the conventional baseline text entry method [49].

In addition, several works have been shown to use device’s accelerometer for text entry to enable eyes-free interaction [107, 204, 238, 267]. For example, Jones *et al.* utilised mobile device accelerometers for text entry using mid-air gestures [107]. The authors showed that accelerometer-based text entry gestures had a significantly higher words per minute rate and a lower error rate. In addition, subjective ratings of the study’s participants showed their preference for accelerometer-based text entry technique [107]. Partridge and colleagues also suggested using accelerometer for text entry, however unlike Jones *et al.* [107], they used accelerometer together with the buttons [204]. This interface was suggested to be used for smartwatches. The combination of the device tilt and pressed button were mapped to a particular character [204].

Moreover, Pielot *et al.* present “PocketMenu” that enables non-visual interaction with the mobile device by locating the menu items on the edge of the touch screen [210]. The system provided a vibrotactile feedback and speech input to enable non-visual interaction. When evaluating “PocketMenu” in comparison with iPhone’s VoiceOver, the authors found that “PocketMenu” outperformed VoiceOver as it was quicker to complete tasks with and had lower selection error rate with higher subjective usability values. The authors propose using “PocketMenu” in situations when the non-visual interaction is needed, such as situational visual impairments, walking, hiking, cycling [210].

Finally, Mariakakis and colleagues implemented “SwitchBack” – a method allowing users to resume tasks in a more efficient manner [154]. The authors used mobile device’s front-facing camera to determine the gaze of the user and based on this information indicated an area on the screen. The method improved user reading speed by 7.7% when the user was distracted. This system enabled easy return of user attention back to a mobile device in presence of distractions of the surrounding environment [154].

Overcoming Privacy Issues

It has been shown in literature that users can be situationally-impaired due to privacy issues [269]; hence, it is important to account for privacy when creating adaptive interfaces to accommodate SIIDs. As such, Lyons and colleagues suggest using dual-purpose speech interaction to overcome privacy challenges when using voice for interacting with mobile devices [147].

A dual-purpose speech serves two roles: 1) it is socially appropriate and meaningful in the context of human conversation; 2) it provides input to a computer. Hence, only the user can be aware of the commands being executed on the device [147].

Buschek and colleagues present "SnapApp" – an unlock concept to reduce authentication overhead by enabling time-constrained quick-access to the mobile device [38]. The technique can be used in situations when the user needs a quick access to the device while having difficulties to unlock it, *e.g.,* while walking or being encumbered. Azenkot and colleagues suggest using tapping sequence to authenticate the user [14]. Precisely, the authors present "PassChords" – an eyes-free touchscreen authentication method based on tap patterns. The authors show that their technique was 3 times faster than the iPhone's standard Passcode Lock with VoiceOver [14]. This technique can be used to enable eyes-free unlock in situations where the visual attention of the user is occupied with another task.

2.2.5 Additional Design Guidelines

This section presents additional design guidelines proposed but not implemented by the respective researchers to potentially overcome different SIIDs.

For example, to diminish the effect of walking on target selection task, Schildbach and Rukzio suggested increasing the button size by a range of 20% and 40% [239]. Moreover, Parhi *et al.* conducted a study aimed at examining the effect of different button sizes on mobile interaction [201]. The study shows that the target selection time and accuracy improve with larger target sizes. The authors argue that target sizes of 9.2 – 9.6 mm is an optimal tradeoff between the target selection time and target size. Nevertheless, the authors suggest taking into account the screen size of the device [201].

Moreover, to decrease the effects of hearing impairments on mobile interaction, both permanent and temporal (caused by SIIDs such as ambient noise), the literature suggests enlarging the cursor [34], using highly visible visual feedback (*e.g.,* flash) to grab user attention [50], and vibrotactile haptic feedback [32]. To reduce the effects of hands motion or tremor on mobile interaction, caused both by permanent impairments of upper limbs and temporal SIIDs caused by *e.g.,* walking, the literature suggests using alternative keyboards, audio input (*e.g.,* voice commands), and eye tracking [151].

Qian *et al.* suggest using tactile notifications to support situationally-impaired users in order to free their visual and auditory attention for other tasks [217]. Furthermore, Yatani and Truong showcased that haptic feedback is effective in supporting eyes-free interaction, as users in their study could distinguish between ten different patterns of tactile feedback with an accuracy of 90% [277]. Similarly, Bragdon *et al.* suggest using Bezel gestures to overcome SIIDs as in their study the authors demonstrate that the environmental factors (*e.g.,* mobility and divided attention) did not have an effect on bezel gestures; hence, the users performed faster and more accurately when interacting with a mobile device [28].

Research has shown that the location on the screen also needs to be taken into account when designing adaptive interfaces to accommodate for different SIIDs. For instance, Wobbrock and Gajos suggest a target selection technique called "goal-crossing" that considers the area around the target as a selection area. As a result it improves target selection accuracy for motor-impaired users and motion-induced SIIDs [272]. Although the authors suggest using the technique for desktop computers, we argue that the method could also be adapted for mobile interaction.

Meanwhile, Kane *et al.* found in their study that the blind users prefer using the edges of the smartphone for the gestures to interact with their mobile device [114]. It is also important to remember that gestures are more preferred when interacting with mobile device as compared to other interaction methods [222]. For example, Reyal and colleagues in their study show the feasibility of gesture-based input keyboard, as their findings demonstrate that the users have a tendency to switch from text-based input keyboard to gesture-based input keyboard [222].

In addition, it is also important to account for different ways to present information as it can benefit interaction when adapting for SIIDs. For instance, Brewster *et al.* suggest using a 3D audio radial pie menu and 2D gestures to facilitate eyes-free interaction [33]. The results of their evaluation show that users were more accurate when provided with an audio-feedback and, hence, improve the usability of mobile devices under eyes-free interaction mode [33].

It is also crucial to provide feedback when designing adaptive interfaces to reduce the effects of SIIDs. Findlater *et al.* formulated design guidelines for touch-screen keyboards that support touch-typing with limited tactile feedback [58]. After investigating typing patterns of 20 professional typists, the authors conclude that creation of effective solutions for non-visual keyboard designs requires personalisation as the key presses were consistent within individual participant [58]. Moreover, Hoggan *et al.* studied the effect of tactile feedback on mobile interaction performance and also showed that tactile feedback significantly improved text entry [98]. Moreover, Hoggan *et al.* suggest taking into account a surrounding environment when providing feedback to the user [99]. The authors empirically show that audio feedback becomes ineffective at noise levels of $94dB$, while tactile feedback become ineffective at vibration levels of $9.18g/s$ [99]. These findings show the importance of the mobile device being able to sense the context to appropriately choose the feedback modality for the user.

In addition, Pielot and colleagues suggest supporting navigation systems with a tactile feedback to free users attention for other tasks from navigating within the environment [208,209]. Qian *et al.* also suggested using tactile feedback to support users during SIIDs in order to free their visual and auditorial channels to complete other tasks that demand their attention [217]. The authors suggest extending their work on to wearable devices to extend the smartphone capabilities [217].

Furthermore, Harper *et al.* suggest using multimodal input that includes combination of oral, visual, audio, and haptic feedback to increase the efficiency of mobile interaction when the participants are experiencing visual impairments [89]. Similar to Harper *et al.* [89], Hoggan and Brewster also suggest using multimodal and crossmodal interaction with mobile devices to substitute visual feedback for mobile notifications [97]. The authors show that participants trained to understand audio alerts could recognise corresponding tactile alerts without any training and vice versa. Therefore, crossmodal features added to the mobile interface elements and hence enable non-visual information about these elements on mobile interface [97].

Pielot and colleagues also suggest using multimodal feedback, including tactile and visual, to improve navigation systems on handheld devices [211]. The authors evaluated their system with 21 participants and have shown combination of the two modalities improved the participants' navigation performance. The authors also show that in the presence of the tactile feedback is used, the user distraction levels decrease [211,212]. Furthermore, in their follow-up work, Pielot and colleagues demonstrate that tactile feedback can be successfully adopted to reduce the effects of SIIDs that appear when using navigation systems (*e.g.*, bright sun light) and, hence, reduce the distraction levels of users [213].

Finally, Barnard *et al.* suggest considering personal characteristics of interaction behaviour, as SIIDs do not affect people in a uniform way [20]. The authors suggest using a combination of hardware sensors, software, and design to overcome the challenges introduced by SIIDs on mobile interaction [20].

2.2.6 Summary

Table 2.1 summarises the findings from section 2.2 in terms of understanding SIIDs including the smartphone tasks used to quantify the effects of SIIDs on mobile interaction, sensing mechanisms used to detect different SIIDs, existing modelling and adapting mechanisms that have been implemented, and other distilled design guidelines recommended by the researchers.

As can be observed from the detailed literature review and stated in [235], the effects of some SIIDs remain underexplored. The literature review also demonstrates that the studies conducted in the field of SIIDs followed an ad-hoc approach, and there were no standard measures and rules to quantify the effects of SIIDs on mobile interaction performance; hence, creating an additional challenge of comparing these effects. We extend this literature by investigating the effects of ambient noise, the effects of stress, and the effects of dim ambient light on mobile interaction in Chapters 4, 5, 6 of this thesis respectively. We also provide a sensing mechanism to detect cold-induced SIIDs in Chapter 8. Finally, we showcase that by following a systematic approach in studying the effects of SIIDs on mobile interaction performance, we can compare the effects of various SIIDs to each other. It is important to note that this table is limited to the SIIDs that have been studied within the research community and includes established findings from the literature. However, a more extensive list of SIIDs that were not yet investigated or acknowledged can be found in [269,273].

Table 2.1: Summary Table of Situationally Induced Impairments and Disabilities in Terms of Their Understanding, Sensing, Modelling, and Adapting

SIID	Understanding		Sensing	Modelling and Adapting Interfaces	Design Guidelines
	Smartphone Task	Effects of SIID			
Walking	Scrolling [115, 149];	Increased error rate [115]; Increased task completion time [115, 149];	Accelerometer [53, 70, 278];	"Cluster Touch" [171]; "ProbUI" [35]; Bezel gesture-based text entry method [102]; "SwipeBoard" [49]; "WalkType" [70]; "ContextType" [71]; "Walking user interfaces" [115]; "Text Text Revolution" [224]; "CATKey" [69]; "NoShake" [219]; Adaptive text entry [95]; Accelerometer-based gestures [107, 202];	Sound feedback for buttons [31]; Change the size of the screen elements [201, 239]; Alternative keyboards using audio input and eye-tracking [151]; Bezel gestures [28]; Increase target selection area [272]; Tactile feedback [211, 212]; Multimodal feedback [89, 97, 211];
	Target acquisition [23, 134, 239];	Increased error rate [134, 239]; Increased workload [134]; Increased target access time [239];			
	Reading (on the device) [51, 173, 239];	Decreased reading speed [173, 239]; Increased cognitive load [239]; Increased task completion time [51];			
	Visual search [90, 173];	Decreased visual search speed [173]; Increased task completion time [173]; Increased cognitive load [90];			
	Text entry [168, 188];	Decreased text entry speed [168]; Increased error rate [188];			
Encumbrance	Target acquisition [182, 184];	Increased error rate [182, 184];	Gyroscope, vibration motor, user touch, swipe shape [72]; "Virtual spring" [85]; "Google Active Edge" [216];	Bezel gesture-based text entry method [102]; "Text Text Revolution" [224]; Dynamic adaptive touch interfaces [37]; Back-of-device interaction [21, 39]; "Fat Thumb" [26]; "ThumbSpace" [116]; "AppLens", "LaunchTile" [117]; "Twiddler" [148]; "Unigesture" [238];	Bezel gestures [28]; Alternative touch interfaces [37];
Encumbrance + Walking	Target acquisition [182, 185];	Decreased walking speed due to encumbrance [182]; Decreased accuracy [185]; Increased target access time [185];			
	Dragging [185];	Decreased accuracy [185]; Increased task completion time [185];			
	Spreading [185];	Decreased accuracy [185]; Increased task completion time [185];			
	Rotating [185];	Increased task completion time [185];			
	Pinching [185];	Decreased accuracy [185];			
Cold ambience	Target acquisition [76, 231];	Increased error rate [76, 231]; Increased target access time [76, 231]; Decreased throughput [76];	Battery sensor [Chapter 8];	n/a	Change the size of the screen elements [201, 231, 239];
	Visual search [231];	No significant effect [231];			

Privacy	n/a	n/a	Accelerometer [87];	Dual-purpose speech interaction [147]; "SnapApp" [38]; "PassChords" [14];	Speech recognition [147]; Non-visual touch interfaces [14] ;
Alcohol	Text entry, Swiping, Simple and Choice reaction tasks [153];	n/a * The authors used these tasks for building predictive models but not to understand alcohol-induced SIIDs on mobile interaction;	Accelerometer, touch-screen [153];	"DUI" to model blood alcohol levels [153];	n/a
Fragmented attention	Browsing task [196, 197];	Decreased attention time to the task [197];	n/a	"SwitchBack" [154];	Bezel gestures [28]; Tactile feedback [208, 209, 211, 212, 217];
Bright ambient light	Visual search [129]; Character detection [139];	Increased search speed [129]; Increased error rate [139];	Accelerometer, ambient light sensor [278];	Colour differentiation models [60]; bezel gesture-based text entry method [102]; "SwipeBoard" [49]; "PocketMenu" [210];	Tactile notifications [217]; Tactile feedback [58, 98, 213, 277]; Using smartphone edges [114]; 3D radial pie menu [33]; 2D gestures [33]; Multimodal feedback [89, 97, 211];
Ambient noise	Target acquisition [Chapter 4] Visual search [Chapter 4] Text entry [Chapter 4]	Increased target access time under music and urban noise [Chapter 4]; Decreased accuracy under music [Chapter 4]; Decreased target memorisation time under urban indoor noise [Chapter 4]; Increased error rate under urban outdoor noise [Chapter 4]; Increased time per character entry under urban outdoor noise and meaningful speech [Chapter 4];	Microphone [219];	n/a	Enlarge a cursor [34]; Provide highly visible visual feedback [50]; Haptic feedback [32];
Stress	Target acquisition [Chapter 5] Visual search [Chapter 5] Text entry [Chapter 5]	Increased target access time [Chapter 5]; Decreased accuracy [Chapter 5]; Decreased target memorisation time [Chapter 5]; No effect	n/a	n/a	n/a

Dim ambient light	Target acquisition [Chapter 6] Visual search [Chapter 6] Text entry [Chapter 6]	Increased target access time [Chapter 6]; Decreased accuracy [Chapter 6]; Increased target memorisation time [Chapter 6]; No effect	Accelerometer, ambient light sensor [278];	n/a	Tactile notifications [217]; Tactile feedback [58, 98, 213, 277]; Using smartphone edges [114]; 3D radial pie menu [33]; 2D gestures [33]; Multimodal feedback [89, 97, 211];

Chapter 3

Methodology

This chapter outlines the methodological approach that was followed in the research presented in this thesis. In particular, it provides the motivation behind particular decisions that were employed in the methodology of the experiments presented in Chapters 4, 5, 6, and 8. The purpose of the studies conducted and presented in Chapters 4, 5, and 6 was to provide an *understanding* of the effects of different situational impairments on mobile interaction; whereas, the purpose of the study presented in Chapter 8 was to introduce a *sensing* mechanism to detect cold-induced SIIDs. All of the experiments conducted within the framework of this thesis were conducted as laboratory studies with strictly controlled settings to avoid causing potential harm to participants and exclude the effect of potential confounding factors.

The focus of the experimental methodology described in this section was to investigate the effects of different SIIDs in a systematic way which allows a fair comparison of these effects between each other. Being able to compare different SIIDs is a crucial step for enhancing SIIDs research [235], as this knowledge is a stepping stone for building appropriate *sensing*, *modelling*, and *adapting* mechanisms that would accommodate the most prominent SIID while at the same time potentially addressing other accompanying SIIDs [256].

3.1 Systematic Approach towards Understanding the Effects of SIIDs

In our systematic approach to investigate the effects of different SIIDs on mobile interaction we have developed an experimental protocol that was reused across multiple studies (Chapters 4, 5, 6). In particular, we re-used the same smartphone tasks to quantify the effects of different SIIDs on mobile interaction. We have also re-used the same observational, scoring, and calculation rules to construct and record dependent variables measuring user performance in mobile interaction under different SIIDs.

We have always followed a within-subject experimental design, in that participants were assigned to all of the conditions in each of the studies, and we also counter-balanced the order of the presentation of the conditions to avoid potential learning effects. In addition, upon the start of the experiment, we briefed our participants about the purpose of the experiment to ensure that each participant was equally informed about the study. In the experiment presented in Chapter 5 we deceived our participants about the true purpose of the study to avoid participant bias and observe natural reaction of participants to stress.

Furthermore, in all of the studies presented in Chapters 4, 5, and 6 we collected baseline measurements of mobile interaction performance upon which the effect of SIIDs were measured. Due to the fact that participant samples in the above-mentioned studies were different, direct comparison of the effects of SIIDs was not possible. However, by contrasting the improvement and/or deterioration in mobile interaction performance for different SIIDs conditions as compared to their relative baseline, we provide a fair comparison of the prominence of SIIDs' effect on mobile interaction. Moreover, we restrict our participants posture for holding smartphone device to perform two-handed interaction: holding a smartphone in a non-dominant hand, while interacting with the smartphone with an index finger of a dominant hand. The holding posture is controlled in order to eliminate the effect of the posture on mobile interaction. At the end of each experiment we held semi-structured interviews with our participants to collect qualitative data to support or contrast collected quantitative data. Hence, based on this methodology we provide a comparison of the magnitudes of the effects of different SIIDs (ambient noise, stress, and ambient light) on mobile interaction in Chapter 7.

3.1.1 Smartphone Tasks

We quantified the effects of different situational impairments on mobile interaction throughout the studies presented in this thesis on three common smartphone tasks (Figure 3.1):

- **Target Acquisition** — Circular targets of similar size ($r = 135px$) randomly appear on different parts of the screen according to $4x6$ grid [92] with a clearly indicated centre one at a time. Participants were asked to press the centre of the targets as quick and as precise as possible. This task measures participants' reaction time (target access time) in milliseconds (ms) and accuracy of the touch (offset size) in pixels.

- **Visual Search** — Application icon is selected at random and shown to the participant for memorising purposes, and then it needs to be found among other 24 icons randomly distributed on the smartphone screen according to $4x6$ grid [92]. This task measures participants' memorisation time in milliseconds (ms), visual search time in milliseconds (ms), and error rate.

- **Text Entry** — A text snippet is displayed on the top of the smartphone screen and participants are asked to type in the text following the case and punctuation. This task measures participants' time per character entry in milliseconds (ms), and total error rate [248].

We argue that these three tasks are the most fundamental in mobile interaction. Before the start of the data collection, our participants underwent extensive training to familiarise themselves with the smartphone tasks. Moreover, the order of the tasks was randomised each time when presented to participants. These steps were necessary to reduce any potential learning effects. We used these tasks to quantify the effects of ambient noise, stress, and dim ambient light on mobile interaction presented in Chapters 4, 5, and 6 respectively. However, in the study presented in Chapter 8 we only used target acquisition task as the purpose of the study was not focused on quantifying the effects of cold ambience on mobile interaction, but to propose a sensing mechanism to detect cold-induced situational impairments.

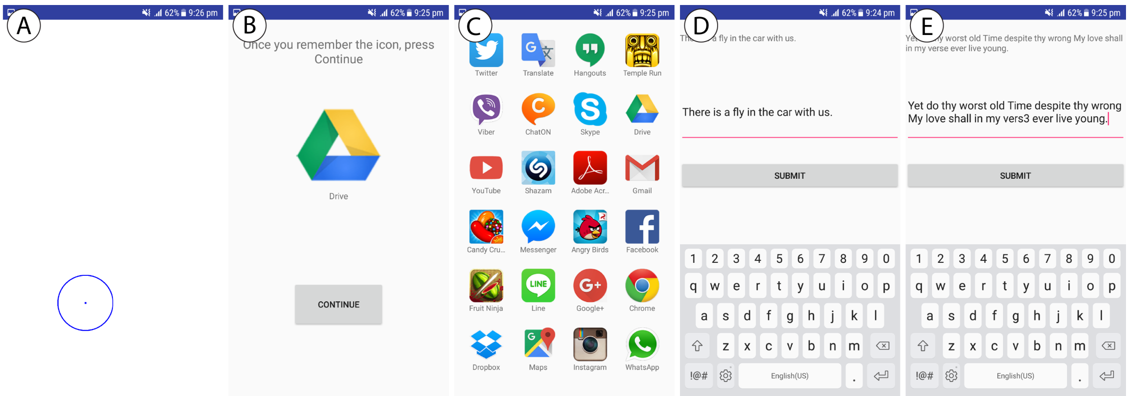

Figure 3.1: Interface of the application with Target Acquisition Task (A), Visual Search Task (B-C), and Text Entry Task with user's input (D-E)

3.2 Data Analysis

We applied a mixed-methods approach, which implies that we utilised both quantitative and qualitative techniques to analyse the data collected in our studies.

3.2.1 Quantitative analysis

Below we provide an overview of the quantitative methods utilised in the data analysis of the research conducted as part of this thesis. We use confidence level of 95% (*i.e.*, $p - value \leq 0.05$) to declare the statistical significance and to reject null hypothesis. This is a common convention used in the discipline of Human-Computer Interaction [127].

In Chapter 4 regarding the effect of ambient noise on mobile interaction, we apply statistical modelling. Statistical modelling in data analysis is used to achieve three main purposes [124]:

- Predict an outcome variable;
- Extract information;
- Describe stochastic structures.

In this chapter we utilise statistical modelling to predict the outcome variable and explain the effect of each of the explanatory variables (predictors) on the dependent variable. To be precise, we built generalised linear mixed effects models to predict variables quantifying user performance (*e.g.,* target acquisition time) based on the predictor variables: fixed (*e.g.,* conditions and other contextual factors) and random effects (*e.g.,* participant). Random effects in generalised linear mixed effects models allows us to account for individual variation among participants, thus allowing us to apply the model to a broader inference about the larger population of participants. Furthermore, statistical modelling allows us to consider many variables that may have an effect on participants' performance during mobile interaction. For example, participant being a native English speaker could have an effect on their mobile interaction behaviour when listening to English speech. Similarly, participants' habit to listen to music while interacting with their smartphones could have an effect on their performance when performing the experiment under the music conditions.

In Chapters 5 and 6 we adopt methods from frequentist statistical inference, namely Analysis of variance, commonly known as ANOVA. In particular, we employ repeated measures ANOVA, as we follow within-subjects experimental design in both of the studies presented in Chapters 5 and 6. Frequentist statistical inference methods are broadly used in HCI research to evaluate the differences in outcome variables under varying conditions [127].

In Chapter 8 we use correlation analysis to understand the relationship between two variables: finger temperature and smartphone battery temperature to evaluate how they behave under the cold ambience. Correlation analysis is also widely employed within the HCI research to describe the type of the relationship and the degree of the dependence between a pair of variables [127]. As the data collected in the study presented in Chapter 8 was normally distributed, we used Pearson product-moment correlation to examine the relationship between the observed and manipulated variables [120].

3.2.2 Qualitative Analysis

Together with the quantitative analysis, we applied qualitative analysis to understand the data collected during semi-structured interviews that we held with participants in the studies presented in Chapters 4, 5 and 6. This approach was applicable to our data analysis as participants' perception and opinions about their performance under various conditions throughout the studies presented in Chapters 4, 5 and 6 was important to us in order to either support or contrast results derived from the quantitative analysis. We did not collect any qualitative data in the study presented in Chapter 8 because we were interested in observing a natural physiological reaction of human finger temperature and smartphone battery temperature to the variations in ambient temperature.

In our qualitative analysis we used two main methods – In Vivo Coding [165] (Chapters 4 and 6) and Thematic Analysis [29] (Chapter 5) – to explain our qualitative data. In Vivo Coding is one of the most common methods used in HCI research to analyse qualitative data [165]. It utilises words and phrases taken from participants' own language and is appropriate for studies that honour participants' voice [165].

The process of performing In Vivo Coding is the following. First, we process the raw data by directly transcribing participants' answers and remarks collected during the interview. Then we identify relevant and repeating concepts and label them with a word or a phrase describing the concept. This allows us to identify clusters and segments related to particular research question, hypothesis, or theme [165].

In Chapter 5 to further enhance our qualitative data analysis, we employ Thematic Analysis following the methodology suggested by Braun and Clarke [29]:

1. We, first, familiarised ourselves with the data.
2. Then we generated codes using In Vivo Coding approach.
3. After that, we identified the themes from the codes.
4. Next, we reviewed these themes.
5. Afterwards, we defined the themes.
6. Finally, we presented the themes as part of the results of the study.

We involved more than one researcher to perform In Vivo Coding and Thematic Analysis to increase the confidence and the validity of the qualitative results [22].

3.3 Ethical Considerations

We accounted for multiple potential issues with our experiments by employing several precautions to manage risks that might have occurred during the studies presented in Chapters 4, 5, 6, and 8. First of all, we assign each participant with an anonymous ID and the collected data is associated with the participant ID only. We ensure that the participants are not directly identifiable. Furthermore, the software used for data collection does not store any sensitive personal information (*e.g.,* name, ethnicity). When storing the data, we use secure servers protected with firewall and control the access to the data through an authentication mechanism. The authentication mechanism requires having a secure password and requests change of the password every 6 months. This is how we solve the issue related to the anonymity of the participants and their data storage.

In each of the studies presented in Chapters 4, 5, 6, and 8 we provided our participants with information in a written Plain Language Statement. Furthermore, each participant's consent was established by signing and returning a Consent Form. We held individual intake sessions with each of the participants where we explained the details of the study and potential risks associated with it. Moreover, participants had the opportunity to read both the Plain Language Statement and a Consent Form before agreeing to participate in the experiment. We commenced the experiment and data collection only after obtaining participant's agreement. Moreover, we excluded any risks that might be harmful to the participants' mental or physical well-being. Precisely, in the work presented in Chapter 4 we limited the sound levels to 55 decibels – an acceptable sound level for everyday life; in the study presented in Chapter 5 we induced mild stress on the participants and excluded involving physical stressors (*e.g.,* electrical shock); in the experiment described in Chapter 8 we exposed our participants to -10°C while providing them with a winter attire. Furthermore, our participants had the right to withdraw from the studies at any point if they wished to do so or felt any discomfort caused by the study protocol.

Finally, we have also accounted for possible dependent relationships between the researchers and participants (*e.g.,* students enrolled in the subjects instructed by any of the research confederates involved in the study) by stating in the Plain Language Statement and in the Consent Form that unwillingness to participate and withdrawal from the study at any point would not have an effect on the students' grades.

3.4 Limitations

The methodology presented in this thesis has several limitations. First, the study settings were strictly controlled. In particular, we ran the experiments under the laboratory settings to provide fair comparison of the effects of SIIDs on mobile interaction performance. Nevertheless, we acknowledge that the effects of SIIDs under the naturalistic conditions could be more prominent [231]. For example, participants in our lab studies experienced certain levels of noise (55 decibels), stress, dim light (20 lux), and cold (-10°C); however, in the real world scenario the levels could have been higher (*e.g.,* louder noise, more stress, darker, and colder environment).

Furthermore, we conducted our studies under a limited number of conditions. For example, in Chapter 4 we used such types of ambient noise as music with fast and slow tempo, indoor and outdoor urban noise, and meaningful and meaningless speech. It is entirely possible that in a naturalistic environment ambient noise types would be more diverse, and multiple noise types could occur simultaneously.

Furthermore, in Chapter 5 we strictly controlled the levels of stress induced on our participants. It is possible that in a real world scenario, participants can be exposed to stronger levels of stress. Nevertheless, it was necessary to strictly control stress induction by following the established protocol to avoid causing harm to our participants, and even a mild incidence of stress was sufficient to adversely affect participant's mobile interaction.

We also acknowledge that across the four user studies presented in this thesis, the number of participants did not exceed 28 people. This sample size might be considered low in other disciplines; however, we followed the local guidelines for the HCI discipline. According to HCI user study standards, the total number of participants above 20 is sufficient to perform statistical analysis [42]. Furthermore, due to the fact that we employed a within-subject experimental design, the statistical power of our analysis increases despite the limited number of participants.

Further to this, we used the same smartphone across the studies presented in Chapters 4, 5, and 6. It is possible that using a different device could have led to a higher variability of the results due to different specifications of the device (*e.g.,* screen contrast, screen size). Nevertheless, we argue that controlling for the device was necessary in order to draw fair comparisons between the effects of different SIIDs on mobile interaction performance.

In addition, in Chapter 6 we examined only two levels of ambient illumination – normal and the dim light, and did not study the effect of bright ambient light (*e.g.,* outdoor illuminance) on smartphone interaction performance. However, this exclusion was necessary to eliminate the effect of additional external factors (*e.g.,* glare) on smartphone interaction performance.

In chapter 8 we limited the room temperature to -10°due to safety concerns. Furthermore, we instructed our participants to not wear gloves or warm their hand by any other means, unlike in naturalistic conditions in order to: 1) avoid touch inaccuracies during mobile interaction; and 2) observe a steady finger temperature drop.

Moreover, the types of smartphone tasks presented in the methodology of this thesis were limited to target acquisition, visual search, and text entry. However, in a more naturalistic setting, users may perform more complex tasks, requiring more cognitive demand. Nevertheless, we argue that these tasks are basic for smartphone interaction, and on a more complex tasks, the effects of SIIDs might be more profound.

Finally, we restricted our participants to only one interaction mode with the smartphone – using the index finger. We argue that controlling the interaction mode was necessary to draw a fair comparison between the effects of ambient noise, stress, and ambient light, while at the same time not making the individual experiments overly long.

3.5 Conclusion

This chapter summarised the primary methodological methods used in the studies presented in this thesis. Overall, it can be concluded that we quantified the effects of different SIIDs on mobile interaction in the laboratory environment with strictly controlled settings to provide fair conditions and comparisons of the effects of different SIIDs on mobile interaction. The aim of the thesis is to quantify the effects of different SIIDs on mobile interaction and contrast their effects as well as to introduce a sensing mechanism to detect cold-induced SIIDs. The following Chapters 4, 5, 6, and 8 present scientific articles on this research topic published at peer-reviewed flagship venues.

Chapter 4

Quantifying the Effects of Ambient Noise on Mobile Interaction

In this chapter we present our work that quantifies the effects of different ambient noise types on mobile interaction. Namely, we asked the participants to complete smartphone tasks (target acquisition, visual search, and text entry) under 4 types of ambient noise conditions:

- Classical music with slow and fast tempo;
- Urban noise – outdoor and indoor;
- Speech – meaningful (in English) and meaningless (in Kazakh);
- Silence, which acted as a baseline condition.

These are four common ambient noise types that might be present during mobile interaction (*e.g.,* , interacting with the smartphone while listening to music, while standing outside near a noisy road, while being involved in a conversation, or in complete silence). Furthermore, these types of ambient noise have previously been shown to influence human behaviour: music tempo can define the speed of human actions [43, 162, 167], urban noise [18, 46] and speech [155, 226] can adversely affect human memory and cognitive performance. However, their effect on mobile interaction has not been previously investigated.

This article shows that when exposed to music with both fast and slow tempo, participants were significantly quicker and less accurate in completing the target acquisition tasks, compared to the silent condition. Our results also demonstrate that when exposed to urban noise conditions, participants were significantly quicker when completing the target acquisition tasks; however, unlike music conditions, urban noise did not affect participants' accuracy in performing the target acquisition tasks. In addition, there was no statistically significant effect of speech conditions on the target acquisition task.

In regard to the visual search task, our findings show that music and speech did not have a statistically significant effect on participants' performance. However, when exposed to the indoor urban noise condition, participants were significantly faster to memorise icons as compared to the baseline condition.

Finally, with respect to the text entry task, our work shows that the meaningful speech condition, dissimilar to music and urban noise, significantly impaired participants' performance. In particular, participants were slower to type in the provided text when listening to meaningful speech when compared to the baseline.

Overall, this chapter investigates the effects of noise-induced SIIDs. Therefore, our work contributes towards accumulating knowledge in SIIDs research. The detailed motivation, analysis, results and discussion of our approach are presented in the attached publication in Section 4.1.

4.1 Publication

Zhanna Sarsenbayeva, Niels van Berkel, Eduardo Velloso, Vassilis Kostakos, and Jorge Goncalves. 2018. Effect of Distinct Ambient Noise Types on Mobile Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 2, Article 82 (July 2018), 23 pages. DOI: `https://doi.org/10.1145/3214285`.

Ethics ID: 1750350.1, The University of Melbourne Human Ethics Advisory Group.

Effect of Distinct Ambient Noise Types on Mobile Interaction

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The adverse effect of ambient noise on humans has been extensively studied in fields like cognitive science, indicating a significant impact on cognitive performance, behaviour, and emotional state. Surprisingly, the effect of ambient noise has not been studied in the context of mobile interaction. As smartphones are ubiquitous by design, smartphone users are exposed to a wide variety of ambient noises while interacting with their devices. In this paper, we present a structured analysis of the effect of six distinct ambient noise types on typical smartphone usage tasks. The evaluated ambient noise types include variants of music, urban noise and speech. We analyse task completion time and errors, and find that different ambient noises affect users differently. For example, while speech and urban noise slow down text entry, being exposed to music reduces completion time in target acquisition tasks. Our study contributes to the growing research area on situational impairments, and we compare our results to previous work on the effect of cold-induced situational impairments. Our results can be used to support smartphone users through adaptive interfaces which respond to the ongoing context of the user.

CCS Concepts: • **Human-centered computing** → Empirical studies in HCI; • **Human-centered computing** → Ubiquitous and mobile computing; • **Human-centered computing** → Smartphones;

Additional Key Words and Phrases: Smartphones, ambient noise, situational impairments, mobile interaction, performance

ACM Reference Format:
Zhanna Sarsenbayeva, Niels van Berkel, Eduardo Velloso, Vassilis Kostakos, and Jorge Goncalves. 2018. Effect of Distinct Ambient Noise Types on Mobile Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 2, Article 82 (June 2018), 23 pages. https://doi.org/10.1145/3214285

1 INTRODUCTION

Research in Ubiquitous Computing has been largely driven by the realisation that the context of use has a substantial influence on the interaction with a system. When non-conventional contextual and environmental factors negatively affect the use of the system, they lead to *situational impairments* [13, 16, 17, 45, 53]. As constant companions for most users, smartphones are frequently used in situations where the user is situationally impaired, *e.g.*, due to cold environments [17], motion [14], or encumbrance [37, 38]. Therefore, one of the key challenges in our community is to enhance the capability of mobile devices to detect situational impairments and to adapt the interaction accordingly.

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2474-9567/2018/6-ART82 $15.00
https://doi.org/10.1145/3214285

In this paper we investigate the effects of one such situational impairment on mobile interaction that remains relatively underexplored [46]—*ambient noise*. Ambient noise is defined as any noise the user is exposed to while their attention is directed at some task or activity [25]. This includes disruptive sounds like the hammering of construction work, the barely perceptive humming of a fridge, the pleasant music playing on headphones, and the disruptive conversation of co-workers. Even though people commonly use their mobile devices in environments where they are exposed to some level of ambient noise (*e.g.*, public places, cafeterias) [25], little is known about their effect on mobile interaction. This paper aims to fill this gap.

Research in Cognitive Science and related fields has highlighted the negative impact that noise has on human behaviour [22, 39], cognitive performance [5, 44, 54], and emotional state [25]. Banbury *et al.* suggest that this effect is mainly caused by the spread of attention while completing a primary task [6]. They state that even if the attention is directed elsewhere, sound is perceived and processed by the brain and, hence, diverts the attention from the main task, causing degradation in performance. Therefore, it is likely that ambient noise can also have an adverse effect on mobile interaction in certain situations. However, due to limited research, it is unclear what is the magnitude of this effect, if there are any differences between different types of noises, and how ambient noise compares to other situational impairments in the context of mobile interaction.

To explore these issues, we investigate how different categories of common ambient noises — *music*, *urban noise*, and *speech* — affect mobile interaction while performing typical smartphone activities: target acquisition, visual search and text entry. To further unpack the effects of the different types of noise, we explore two variants of each. We presented users with *slow* and *fast* tempo music, as previous work has shown that different music tempos have varying effects on cognitive performance [22, 39]. We also presented users with two types of urban noise: *outdoor* and *indoor*. Outdoor urban noise has been shown to have a significant adverse effect on memory tasks. However, there is no consensus regarding the effect of indoor urban noise: some studies report its distracting effect during memory tasks [5, 54], while others did not observe any effect on cognitive performance [44]. Finally, we presented users with two types of speech: *meaningful* and *meaningless* speech. Meaningful speech is speech spoken in a familiar language, whereas meaningless speech is defined as the speech presented in a language unfamiliar to the listener [32]. To contextualise our study within the body of research on situational impairments, we compare our findings to previous work on cold-induced situational impairments [45], which collected similar data to the one described in our study.

In summary, this paper advances the state-of-the-art on situational impairment research in Ubiquitous Computing through three main contributions. First, we investigate how different types of ambient noise affect the interaction with mobile devices during three typical activities: target acquisition, visual search, and text entry. Second, we contribute towards the situational impairments research agenda by comparing our findings to the effects of cold-induced situational impairments. Third, we discuss and provide recommendations on the detection of certain types of ambient noise that can affect mobile interaction and how to accommodate a situationally impaired user in such cases.

2 RELATED WORK

2.1 Impact of Situational Impairments on Mobile Interaction

Previous research has shown that interaction with mobile devices can be adversely affected by implicit environmental and contextual factors, subjecting the user to what is known as a *situational impairment* [46, 49]. A number of causes for situational impairment have been studied within the HCI/UbiComp community, including the effects of ambient temperature [17, 45], motion [14], and encumbrance [37, 38]. Regarding cold-induced situational impairments, Goncalves *et al.* and Sarsenbayeva *et al.* showed a negative effect of cold temperatures on smartphone input performance [17, 45]. The authors found that colder temperatures are associated with lower throughput and accuracy in tapping tasks. Other studies investigated the effect of user motion on interaction with mobile phones. For example, walking has been found to adversely affect mobile interaction in completing typing tasks [14, 36], and target acquisition tasks [48]. Furthermore, Ng *et al.* [37, 38] demonstrated the negative impact of encumbrance on target acquisition tasks during mobile interaction. In particular, encumbrance has been shown to decrease accuracy, while increasing error rate and target selection time [38]. Given the effect situational impairments have on mobile interaction, previous work was conducted to explore ways of detecting situational impairments and develop design solutions to accommodate them. For example, Sarsenbayeva *et al.* [47] suggest using smartphone's battery temperature to detect ambient temperature drop. Similarly, Goel *et al.* [14] successfully utilise a smartphone's accelerometer sensor to detect walking. In terms of design solutions, researchers have shown that increasing target size [48], providing audio guidance [52] and adaptive text entry [14] can compensate the negative effect of situational impairments.

In comparison to other causes of situational impairment, the effect of ambient noise on mobile interaction lacks appropriate investigation [46]. Previous work emphasises the importance of studying unexplored causes of situational impairment in order to broaden the research scope in this area [46]. There is little prior work that has studied the effect of ambient noise on mobile interaction. A study by Hoggan *et al.* [21] showed that loud noise levels had an adverse effect on participants' performance when completing text entry tasks on mobile phones. However, the aim of their study was simply to identify the noise threshold at which the audio and tactile feedback become ineffective. Harvey & Morgan [18] demonstrated that noisy environments have a negative effect on user performance during web search tasks. They showed an effect of noise on task performance using questionnaire data only and did not provide any quantitative metrics regarding performance. To the best of our knowledge, this is the first study to investigate and quantify the effect of ambient noise as a potential cause of situational impairment during mobile interaction.

2.2 Effect of Ambient Noise on Human Behaviour and Cognitive Performance

Previous work has shown that ambient noise has an effect on human daily activities in terms of behavioural [29, 33, 39], emotional [25], and cognitive [5, 54] performance. As mobile interaction is now an essential part of people's everyday activities, it is important to investigate its impact on mobile interaction. Next, we discuss related work on the impact of music, urban noise and speech on human behaviour and cognitive performance.

2.2.1 Effect of Background Music on Human Behaviour and Cognitive Performance. Previous works have investigated the effect of music on people's physical activities [33], cognitive performance [26], and mood [25]. Cassidy *et al.* showed a significant negative effect of heavy metal music on immediate recall, free recall, delayed recall and performance in Stroop tasks [15] compared to a silent condition [10]. Similarly, Wen *et al.* demonstrated that performance in recall is significantly higher under classical music in contrast to rock music [55]. However, there is no consensus regarding the effect of background music on reading [25]. Whereas some studies report an increase on reading performance [41], other studies failed to replicate this effect [32]. Another study showed that slow tempo music resulted in longer reading time and poorer reading efficiency in contrast to fast tempo music [25]. Henderson *et al.* 's results suggest that what is detrimental is not the music itself, but the speech contained in it [19]. The authors found that participant performance in completing reading tasks significantly decreased when they were exposed to popular music containing lyrics, but found no significant decrease with classical music or silence [19]. Given these results, we evaluate the effects of music and speech in separate study conditions.

The most widely studied musical element in terms of the effect of music on human behaviour and cognitive performance has been the *tempo*, *i.e.,* the speed of the underlying beat of the music. Related work suggests that the faster the tempo, the faster people complete tasks. Milliman showed that faster tempo increased the walking speed of customers, decreasing the average time customers spent in a store [34]. Research in restaurants and cafeterias has shown that faster music also caused people to eat and drink faster [9, 33, 35]. Conversely, slower music was shown to slow down people's eating and drinking [9, 33, 35] as well as to prolong the perception of elapsed time spent in casinos [40].

Despite accelerating task completion, previous research suggests that music with a faster tempo is also more cognitively demanding. For instance, Holbrook showed that fast tempo music demanded more cognitive resources to be processed compared to slow tempo music [22]. According to North *et al.* , this phenomenon occurs because more information is perceived and processed by the listener's brain when fast tempo music is played than when slow tempo music is played [39]. Given the different effects of the tempo of the music, we evaluated the effect of music on mobile interaction with fast and slow tempo music.

An interaction effect between the tempo of the music and the gender of the listener has also been identified. For example, Kallinen showed that female and male participants perceived information differently under slow and fast music conditions [25]. In this study, the author found an inverse effect of the tempo of the music on the perception of news articles — a slow tempo led male participants to evaluate the news as negative, whereas it led female participants to evaluate the same set as positive. Further, men read more slowly when slow tempo music was playing, whereas women read more slowly when no music was playing. This suggests that it is important to ensure appropriate gender balance in the participant sample to avoid any gender bias in the results.

Taking into consideration the effect of music tempo on other aspects of human behaviour and cognitive performance, we chose to investigate its effect on mobile interaction. We hypothesise that fast tempo music will result in a faster completion of tasks when compared to the silent condition, particularly those that require fine-motor movements (*e.g.,* target acquisition tasks).

2.2.2 Effect of Urban Noise on Human Behaviour and Cognitive Performance. As with background music, urban ambient noise is also known to influence human behaviour and cognitive performance. In this study, we focus on two types of urban noise: outdoor and indoor. We define outdoor urban noise as noise containing sound as sampled in an urban area: a combination of street, construction, and traffic sounds. We define indoor urban noise as the noise coming from an office or cafeteria: working sounds, people's murmur, and chatter.

A negative effect of urban outdoor noise on human performance has been shown in several studies. For example, Cassidy *et al.* showed a significant negative effect of outdoor urban ambient noise on free, immediate, and delayed recall and Stroop tasks [15] when compared to no noise [10]. Furthermore, Stansfeld *et al.* showed that communities exposed to lower traffic noise had a lower rate of psychiatric hospitalisation [50]. Previous work has also shown that an exposure to a broadband noise at 100 dB for 30 minutes can lead to significant impairments when performing memory tasks [2].

Regarding urban indoor noise, Banbury and Berry demonstrated that students' performance in completing mathematical and recall tasks was significantly worsened with its presence [5]. Furthermore, a two-year longitudinal study by Cohen and Weinstein showed that children in noisy schools with sound levels of 60-80 dB performed worse in solving puzzles and mathematical tasks [11], as reported by Holmberg and Coon [23].

This literature coupled with the fact that it is common practice for mobile device users to interact with their devices while being exposed to urban outdoor (*e.g.,* streets) and indoor (*e.g.,* office, cafeteria) noise, suggests that these types of noises can have an effect on mobile interaction, which we investigate in this paper.

2.2.3 Effect of Speech on Human Behaviour and Cognitive Performance. Previous research has made a distinction between the effects of two types of speech on human behaviour and cognitive performance [32]: *meaningful* — speech that the listener can understand — and *meaningless* — speech that the listener does not understand. For instance, Martin *et al.* found a detrimental effect of continuous meaningful speech on reading performance when compared to silence [32]. The authors compared the effect of meaningful and meaningless speech on reading comprehension and showed that reading performance is significantly worse under both speech conditions as compared to silence, with a stronger effect for meaningful speech [32].

Previous work has also shown that both meaningful and meaningless speech have an equally distracting effect on memory recall [51]. Tremblay *et al.* found that natural speech was more disruptive than sine wave speech (*i.e.,* a form of artificially degraded speech) on tasks requiring memory recall [51]. Moreover, in a study reported in [43] meaningless speech was shown to have a negative effect on memory tasks. Salame *et al.* showed that immediate memory was disrupted the most by the the unattended foreign language speech, when compared to other conditions such as instrumental music, urban noise and silence [44]. These results contradict previous findings that did not find any effect of meaningless speech on cognitive performance in phonological judgement tasks [3]. Nevertheless, the authors argue that the phenomenon needs further investigation [3]. Finally, speech is also known to reduce performance in completing arithmetic tasks and memory for prose tasks [4, 54].

In this paper we explore the effect of both meaningful (English) and meaningless (Kazakh) speech on mobile interaction. Based on the literature, we hypothesise that the performance in tasks with higher cognitive requirements (*e.g.,* text entry) is likely to deteriorate while hearing background speech.

3 STUDY

We operationalise mobile interaction in terms of three common activities conducted on smartphones: target acquisition, visual search, and text entry. For this study we used two software applications as experimental tasks, *TapCircle* and *FindIcon*, previously used to investigate the effect cold-induced situational impairments on mobile interaction [45]. This allows for direct comparison of our results to those previous findings. Additionally, we developed a new custom software called *TypeMe*. The tasks presented by TapCircle measures users' fine-motor performance during target acquisition, the task in FindIcon measures users' cognitive performance during visual search [45], and the task in TypeMe measures users' text entry performance. The three tasks were combined into one Android application and were presented in a random order. Details for each task are presented below, the application interface is shown in Figure 1.

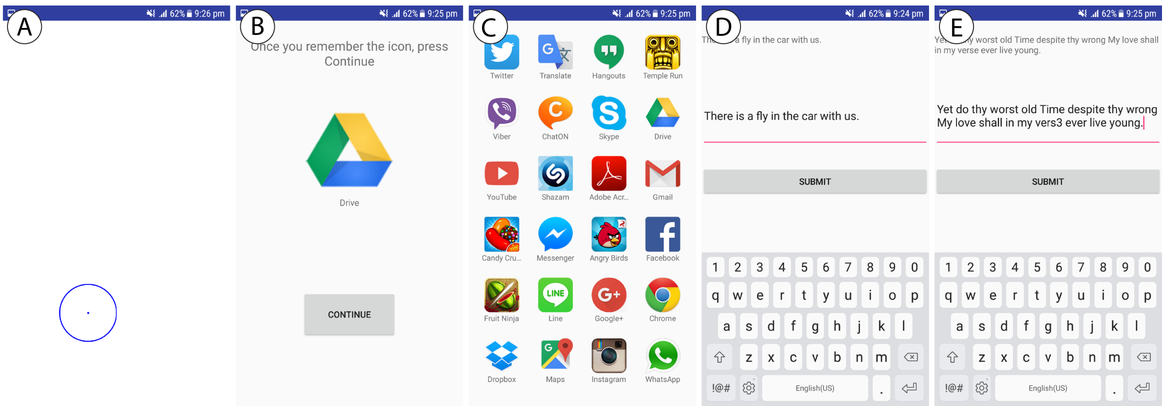


Fig. 1. Interface of the application with TapCircle task (A), FindIcon task (B-C), and TypeMe task with user's input for easy and difficult texts (D-E)

3.1 Tasks

3.1.1 Task 1: Target Acquisition. Circular targets with a radius of 135 pixels randomly appear one at a time in each position of a 4×6 grid at least once. A similar task was used by Henze *et al.* [20]. Every target has an indicated centre and participants were instructed to tap these circles as quickly and as precisely as possible. The application logged the coordinates of the target's centre and participant's touch point, the elapsed time, and the position of the circle on the grid. Figure 1-A shows a screen of the TapCircle task interface.

3.1.2 Task 2: Visual Search. In the FindIcon task, participants were first presented with an icon which they subsequently had to locate within a grid of other icons. Participants were free to look at the target icon for as long as they wanted to memorise it. In the following screen, participants were required to locate and tap the target icon amongst a set of 24 icons (100×100px) in a 4×6 grid. To minimise any possible learning effects, each of the 24 icons was designated as a possible target icon in random order in each condition. The application also ensured that every grid position hosted a target icon in a random order. To make our results comparable, we used the same set of application icons as described by Sarsenbayeva *et al.* [45]. Figures 1-B-C show the interface of the task. The application recorded time spent on memorising an icon, time spent on locating and tapping the target icon, grid position of the icon, and the coordinates of the centre of the icon and of the participant's touch point.

3.1.3 Task 3: Text Entry. In the text entry task, the application presented some text at the top of the screen and participants were asked to type it verbatim in the text-box below it. In order to have varying complexity, we distinguished between easy and difficult texts. Easy texts consisted of only one sentence and contained common words that are used on a daily basis. Difficult texts were selected from Shakespeare's sonnets and consisted of more than 1 sentence. We quantified the difficulty of the sentences using the Flesch-Kincaid readability test [28]. The easy texts had an average Flesch-Kincaid grade level of 1.6, whereas the difficult texts had an average Flesch-Kincaid grade of 5.1. Participants completed both an easy and a difficult text during the task. Figures 1-D-E show the task as presented to the participants, including examples of an easy and a difficult text.

3.2 Hardware

Participants completed all tasks using a Samsung Galaxy S7 smartphone running Google's Android 7.0 (Nougat). The smartphone has a 5.1-inch screen with a resolution of 1080×1920px. The smartphone was selected due to identical screen size and resolution to the smartphone's screen parameters used in Sarsenbayeva *et al.*'s evaluation of cold-induced situational impairments [45]. This allowed us to directly compare the effects of noise-induced situational impairments to cold-induced situational impairments on mobile interaction.

3.3 Experimental Conditions

We selected the following experimental ambient noise conditions for this study given their demonstrated effect on human behaviour and cognitive performance in the literature:

- music (fast and slow tempo)
- urban ambient noise (indoor and outdoor)
- speech (meaningful - English, meaningless - Kazakh)
- silence, which acted as a control condition.

In the music conditions we used the same composition sampled at fast and slow rates to avoid other characteristics of the music, other than tempo (*e.g.,* pitch, timbre), to affect the participants performance. This is because tempo is considered to be the main factor in music to affect human behaviour and performance [25]. We chose music that did not contain any lyrics in order to avoid overlap with the speech condition. Given these guidelines, we selected Bach's "Brandenburg Concerto No. 2". As the original tempo of the composition is considered to be fast (92 beats per minute) [25], we used it as is for the fast tempo music condition. For the slow tempo music condition we sampled the same composition at 60 beats per minute, below the 70 beats per minute considered in the literature to be slow [25], without any noticeable decrease in sound quality.

As for the urban outdoor ambient noise condition, we chose a clip of street noise containing road traffic, vehicles' motor sounds, honking, and indistinguishable crowd speech. For the urban indoor condition we chose a cafeteria noise composed of coffee machine, cutlery sounds, and indistinguishable people's murmur. Both of the sounds were obtained from YouTube (urban outdoor [1], urban indoor [2]).

For the meaningful speech condition, we selected a weather forecast presented in English. For the meaningless speech condition we selected TV news presented in a language that participants did not understand (Kazakh). Both clips were narrated by a female voice and did not contain any other sounds (*e.g.,* background noise, music, speech of different people).

The volume level for all of the ambient noise conditions was kept in the range of 55–60 dB following Iwanaga and Ito's design guidelines, to avoid discomfort to our participants [24]. All audio files were long enough for participants to complete all tasks before the audio clip ended.

3.4 Participants and Procedure

We recruited twenty-four participants (12 male, 12 female) through our university's mailing lists. We balanced gender as the literature suggests men and women can react differently to the same noise conditions [25]. Participants were aged between 19 and 54 years (M = 31.67, SD = 8.95) and had a diverse range of educational backgrounds (*e.g.,* Accounting, Geology, Linguistics, Biochemistry, Computer Science, Elderly Care). All participants were fluent in English and used it as their main language of communication at work. The foreign language presented in this study ('meaningless speech') was not known to any of the participants. Each participant was assigned a unique anonymous ID (participant ID) in our study.

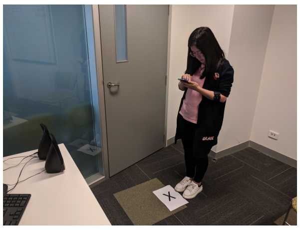
Our study had a within-subjects experimental design. Condition acted as an independent variable and the order of conditions presented to the participants was counter-balanced. This way, we minimised the impact of any potential fatigue or learning effects. Unlike the study protocol presented in [45], participants completed all tasks in only one smartphone holding posture as opposed to two different holding postures. We instructed our participants to complete all tasks in two-handed interaction mode while standing (*i.e.,* interacting with the phone with index finger of the dominant hand while holding the phone in the non-dominant hand [45]). Figure 2 shows the participant completing a task during the experiment. As each participant was required to complete three tasks in each of seven conditions, including a second smartphone holding posture (and essentially doubling study duration) would have likely introduced considerable fatigue and irritation among our participants. Each participant was rewarded with a $10 voucher for participation.

We collected data for several dependent variables to measure performance while conducting the tasks. In the target acquisition task, we recorded the time taken to tap a circular target and the size of the tap offset. In the visual search task, we recorded the time taken to find the correct icon, the time taken to memorise an icon, and the number of incorrectly selected icons. Finally, in the text entry task, we recorded the time taken to complete typing a text, the number of characters per text, and the number of errors within the text that were not corrected by participants. We measured the typing performance with the time taken per character entry by dividing the total typing time by the number of characters per text.

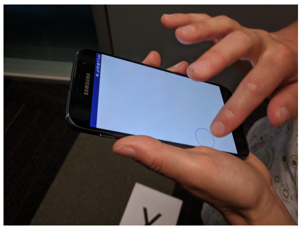
Upon arrival at our usability lab, participants were briefed about the purpose of the study and asked to sign a consent form. We then collected their personal details (age, gender, background, native language, dominant hand) and performed a training procedure in order for the participants to get acquainted with the tasks. During the training, participants completed all three study tasks in a random order, until they were comfortable with each one, in order to minimise any potential learning effects.

Once the training was completed, participants started the experiment. As the study contained four main conditions (silence, music, urban noise, speech), we created 24 combinations of the conditions to ensure proper counter-balancing. This means that no participant had a repeated order of conditions presented to them. Three

[1]https://www.youtube.com/watch?v=cDWZkXjDYsc
[2]https://www.youtube.com/watch?v=lSlOXT3AKBo



(a) Laboratory setting of the experiment



(b) Smartphone holding posture

Fig. 2. Participant completing tapping circles task

of the conditions included sub-conditions (music fast/slow tempo, urban noise outdoor/indoor, speech meaningful/meaningless). We randomly allocated the participants into two groups. Within each of these conditions, the first group was exposed to fast music tempo, indoor urban noise, and meaningful speech conditions first. The second group, opposite to the first group, was exposed to slow music tempo, outdoor urban noise, and meaningless speech first. Both groups experienced both sub-conditions.

During the experiment, participants had to complete the same set of tasks in each of seven conditions. Each round of tasks consisted of: target acquisition, visual search, and text entry. The order of the tasks was randomised by the application, and the participants had to complete each task one after another without taking any breaks. Once the sound of a condition started playing, the researcher started a timer. After being exposed to the sound for one minute, the participant was then instructed to begin that round of tasks. Listening to the sound for one minute ensured participants were more accustomed to that particular ambient noise condition [17, 45].

After the experiment was completed, we conducted a short semi-structured interview. Participants were asked about their personal perception of their performance during the conditions, whether any of the sounds were experienced as particularly distracting, and whether they usually listen to music or any other sounds while working, reading, or performing tasks that demand concentration. Finally, we enquired if they listen to music or other type of audio when they interact with their smartphones. The experiment lasted approximately 70 minutes per participant, including briefing, training, data collection, and final interview.

4 RESULTS

From our 24 participants, we collected 15,556 and 4,094 target hits for the tapping the circles and finding icons task respectively, and 336 typed sentences for the typing task. Data collected from left-handed participants ($N = 2$) was mirrored relative to the X-axis of the screen for the tapping a circle and finding an icon tasks.

To investigate whether mobile interaction was affected by ambient noise, we built generalised linear mixed-effect models to describe participant performance in the three tasks (target acquisition, visual search, and text entry). Apart from the ambient noise conditions (discussed in Subsection 3.3), we also considered other factors that may affect participants' performance during mobile interaction. We provide a list of these variables below. Unless otherwise stated, the variable was included for all conditions (silence, music, urban noise, and speech).

- **Gender** - A binary variable indicating gender of the participant.
- **Age** - A numeric variable indicating the age of the participant.
- **Music listener** - A binary variable indicating whether the participant typically listens to music or other sounds while working, reading, or performing tasks that require cognitive demand. We only used this predictor in models predicting the effect of music on mobile interaction.

- **Native English speaker** - A binary variable indicating if the participant is a native English speaker. We only used this predictor in models predicting the effect of speech on mobile interaction.
- **X centre coordinate** - X-axis coordinate of the centre of target (circle or icon for tapping a circle and finding an icon task respectively).
- **Y centre coordinate** - Y-axis coordinate of the centre of target (circle or icon for tapping a circle and finding an icon task respectively).
- **Participant ID** - Participant ID was treated as a random effect in order to control for individual differences in our models.

We applied a backfitting algorithm using AIC to all our models for predictor selection. AIC penalises the inclusion of additional predictors, which could lead to overfitting of a model. Finally, to ensure the validity of the models we checked for the presence of multicollinearity. All of the predictors for each of the presented models had a variance inflation factor between 1 and 1.38, well below the often used threshold of 5 to 10 to detect multicollinearity.

4.1 Results: Background Music Condition

The tested background music conditions are fast tempo music, slow tempo music, and silence. The conditions are tested across all three defined tasks. We discuss the results per task below.

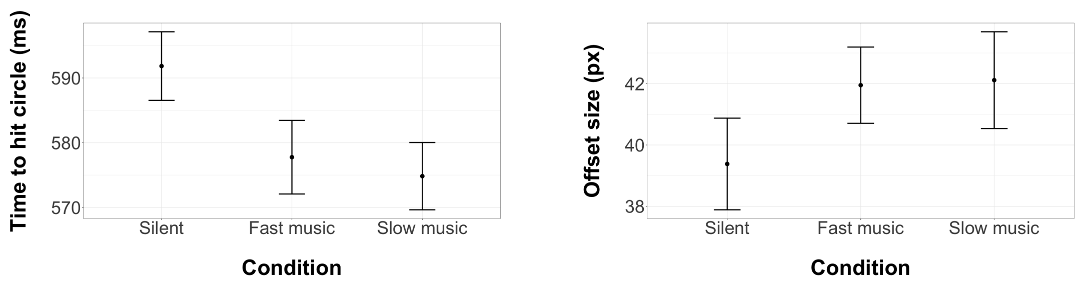
4.1.1 Target Acquisition. Our first model describes the time taken to hit a circle. The final prediction model retained 3 of the 6 predictors, as shown in Table 1. The model is statistically significant ($\chi^2(4) = 56.05$, $p < 0.01$) and describes 7% of variance of the time taken to hit the circle ($Marginal\ R^2 = 0.07$, $Conditional\ R^2 = 0.28$). The results indicate that participants were significantly quicker to tap circles in the fast and slow music conditions as compared to the silent condition. However, we did not find a significant difference between the fast and slow music condition; Wilcoxon signed-rank test ($V = 1.17e{+}06$, $p = 0.21$). A boxplot of the time taken to complete the tapping circles task across the different conditions is shown in Figure 3 (a).

Table 1. Effects of model factors on predicting time taken to hit a circle in music condition

	Estimate	**Std. Error**	**t value**	**Pr (>|t|)**
(Intercept)	4.63e+02	4.55e+01	10.19	7.68e-10 ***
Condition (Fast music)	-1.51e+01	3.41	-4.43	9.61e-06 ***
Condition (Slow music)	-2.01e+01	3.41	-5.91	3.71e-09 ***
Y centre coordinate	8.76e-03	2.62e-03	3.35	0.001 ***
Age	3.98	1.38	2.89	0.008 **

Significance: '***' <0.001, '**' <0.01, '*' <0.05

Mean values for the offset size per condition for the tapping task are visualised in Figure 3 (b). We built a model to describe the mean offset size when tapping a circle. The final model contains both conditions and the X centre coordinate as predictors, and is summarised in Table 2. The model was significant ($\chi^2(4) = 63.43$, $p < 0.01$, $Marginal\ R^2 = 0.01$, $Conditional\ R^2 = 0.10$). Participants were significantly less accurate when tapping the circles in the slow music condition as compared to the silent condition. A Wilcoxon signed-rank test did not show a significant difference between the offset size in the fast tempo music condition and the slow tempo music conditions ($V = 1183600$, $p = 0.21$). From Table 2, we observe that the offset is smaller for the circular targets located closer to the edge of the screen on which participants held their phone.



(a) Time taken to tap a circle

(b) Offset size

Fig. 3. Mean values for time taken to tap a circle and offset size per condition

Table 2. Effects of model factors on predicting the offset size when tapping a circle in music condition

	Estimate	**Std. Error**	**t value**	**Pr (>|t|)**
(Intercept)	4.47e+01	2.22	20.17	<2e-16 ***
Condition (Fast music)	1.58	1.01	1.57	0.12
Condition (Slow music)	2.74	1.01	2.72	0.007 **
X centre coordinate	-1.01e-02	1.34e-03	-7.52	6.22e-14 ***

Significance: '***' <0.001, '**' <0.01, '*' <0.05

4.1.2 Visual Search. Next, we built a model to describe the time taken to memorise an icon. The final prediction model contained only age as a predictor. The direction of age was negative, indicating that younger participants took less time to memorise an icon. The model was statistically significant ($\chi^2(1) = 12.26$, $p < 0.01$) and described 9% of variance of time taken to find an icon ($Marginal\ R^2 = 0.09$, $Conditional\ R^2 = 0.22$).

We built another model to describe the time taken to find an icon. The final model again contained only age as a predictor, and direction was again negative (indicating that younger participants took less time). The model was statistically significant ($\chi^2(1) = 18.22$, $p < 0.01$) and described 2% of variance of the time taken to find an icon ($Marginal\ R^2 = 0.02$, $Conditional\ R^2 = 0.08$).

Finally, we built a model to describe the number of errors made by participants when finding an icon. However, none of the predictors sufficiently described this dependent variable. We were thus unable to create a model for this variable.

4.1.3 Text Entry. The last task for the background music condition is the typing task. We built a model to predict the time per character entry. However, we were unable to create a model for this variable as none of the predictors sufficiently described it.

Following this, we build a model to describe the number of errors made by participants when typing a message. The final model contained one predictor (participant age). Participants of younger age made fewer errors. The model was statistically significant ($\chi^2(1) = 8.55$, $p < 0.01$) and described 12% of variance of the number of uncorrected errors ($Marginal\ R^2 = 0.12$, $Conditional\ R^2 = 0.31$).

4.2 Results: Urban Noise Condition

The tested urban noise conditions are outdoor, indoor, and silence. The conditions are tested across all three defined tasks. We discuss the results per task below.

4.2.1 Target Acquisition. We first built a model to describe the time taken to tap a circle. The final model was described with three predictors: condition, Y centre coordinate of the circle, and participant age. We provide a summary of the factors in Table 3. The model was statistically significant ($\chi^2(4) = 54.73$, $p < 0.01$) and described 8% of variance of the time taken to tap a circle ($Marginal\ R^2 = 0.08$, $Conditional\ R^2 = 0.27$). Participants took significantly less time to tap a circle in both indoor and outdoor noise conditions, with the stronger effect of urban outdoor noise. Wilcoxon signed-rank test did not show a significant difference between the indoor and outdoor noise conditions for time taken to tap circle ($V = 1.26e{+}06$, $p = 0.81$). We visualised mean values for the time taken to tap a circle per condition in Figure 4. Table 3 shows that older participants required more time to tap a circle, similar to our observation in the music conditions. Furthermore, we show that the further from the top left corner the target is, the longer the target acquisition time is.

Table 3. Effects of model factors on predicting time taken to tap a circle in urban noise condition

	Estimate	**Std. Error**	**t value**	**Pr (>|t|)**
(Intercept)	4.68e+02	4.03e+01	11.61	6.42e-11 ***
Condition (Indoor noise)	-7.89	3.09	-2.55	0.011 *
Condition (Outdoor noise)	-19.4	3.12	-6.21	5.65e-10 ***
Y centre coordinate	6.33e-03	2.37e-03	2.67	0.007 **
Age	3.85	1.22	3.14	0.005 **

Significance: '***' <0.001, '**' <0.01, '*' <0.05

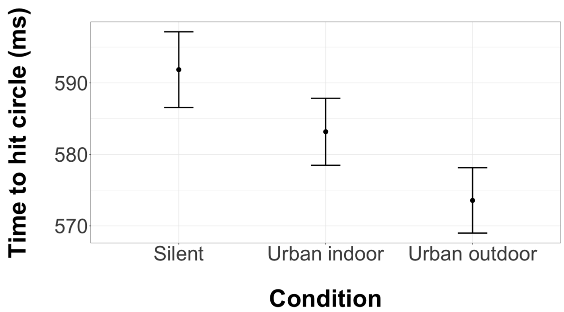


Fig. 4. Mean values for time taken to hit a circle per condition

We then built a model to predict the offset size. The final model contained the X centre coordinate of a circle as its only predictor. The direction of the predictor is negative, indicating that the closer to the right edge of the screen the circle is located, the smaller the offset of the touch is. The model was statistically significant ($\chi^2(1) = 33.77$, $p < 0.01$) describing 0.5% of variance of the offset size ($Marginal\ R^2 = 0.005$, $Conditional\ R^2 = 0.07$).

4.2.2 Visual Search. To check the effect of the urban noise conditions on performance during icon search task, we built a model to predict the time taken to memorise an icon. The final model contained two predictors: condition and participant age. The model was significant ($\chi^2(3) = 21.33$, $p < 0.01$) and described 8% of variance of time taken to memorise an icon ($Marginal\ R^2 = 0.08$, $Conditional\ R^2 = 0.22$). The coefficients of the predictors are summarised in Table 4. From the table, we observe that participants spent significantly less time memorising an icon in the urban indoor noise condition compared to the silent condition. However, the effect of urban outdoor condition did not significantly affect the time taken to memorise an icon. Mean values for time taken to memorise an icon per condition can be found in Figure 5.

Table 4. Effects of model factors on predicting time taken to memorise an icon in urban noise condition

	Estimate	**Std. Error**	**t value**	**Pr (>|t|)**
(Intercept)	510.38	69.36	7.36	2.01e-07 ***
Condition (Indoor noise)	-36.48	12.33	-2.96	0.003 **
Condition (Outdoor noise)	-5.18	12.32	-0.42	0.67
Age	7.55	2.10	3.593	0.002 **

Significance: '***' <0.001, '**' <0.01, '*' <0.05

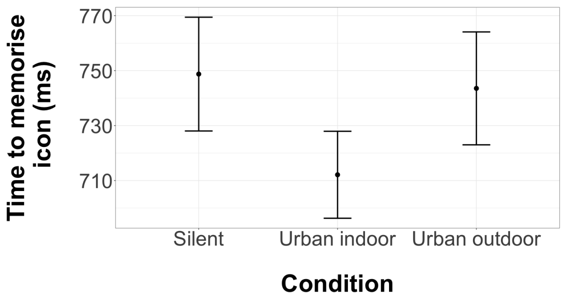


Fig. 5. Mean values for time taken to memorise an icon per condition

Next, we built a model to describe the total time taken to find an icon in the urban noise conditions. The final model contained the X centre coordinate of the icon as its only predictor. The predictor was again negative, indicating that the icons were quicker to find the closer they were located to the right edge of the screen. The model was statistically significant ($\chi^2(1) = 9.32$, $p < 0.01$) and described 0.5% of variance of time taken to find an icon ($Marginal\ R^2 = 0.005$, $Conditional\ R^2 = 0.09$).

Finally, we built a model to describe the number of errors made by participants in the finding an icon task. The model was described with three predictors; condition and both the X and Y centre coordinates of the icons. The model was statistically significant ($\chi^2(4) = 16.45$, $p < 0.01$) and explained 1% of variance of the number of errors participants performed during icon search task ($Marginal\ R^2 = 0.01$, $Conditional\ R^2 = 0.04$). The model is summarised in Table 5.

Table 5. Effects of model factors on predicting errors in finding an icon in urban noise condition

	Estimate	**Std. Error**	t value	Pr(>|t|)
(Intercept)	1.89e-02	1.63e-02	1.16	0.25
Condition (Indoor noise)	6.44e-03	1.19e-02	0.54	0.59
Condition (Outdoor noise)	2.60e-02	1.19e-02	2.18	0.03 *
X centre coordinate	-4.42e-05	1.71e-05	-2.59	<0.01 **
Y centre coordinate	2.08e-05	9.90e-06	2.10	0.04 *

Significance: '***' <0.001, '**' <0.01, '*' <0.05

The mean values for the number of errors in the icon search task are visualised in Figure 6. According to our findings, participants were significantly less accurate in the urban outdoor noise condition when compared to silent condition. The effect of X and Y centre coordinates is again in line with our previous findings.

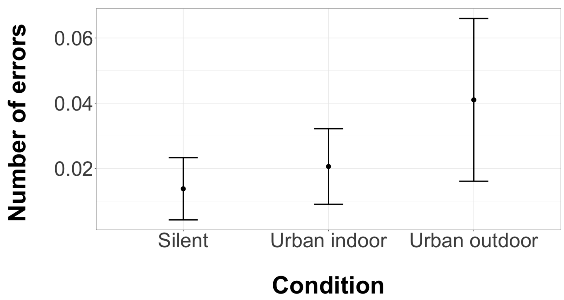


Fig. 6. Mean values for errors in find an icon task per condition

4.2.3 Text Entry. We then built a model describing the time required per character entry. The final prediction model contained both condition and gender as predictive variables. The model was statistically significant ($\chi^2(3) = 10.79$, $p = 0.01$) and explained 14% of variance of the time per character entry participants spent during the typing task ($Marginal\ R^2 = 0.14$, $Conditional\ R^2 = 0.49$). We presented the summarised model in Table 6. We then visualised the values of the mean time per character entry in a boxplot in Figure 7. Finally, we built a model to predict the number of errors made by participants during the typing task. None of the included predictors sufficiently describe this variable.

Table 6. Effects of model factors on predicting time per character entry in a typing task in urban noise condition

	Estimate	**Std. Error**	t value	Pr(>|t|)
(Intercept)	376.59	47.16	7.99	5.17e-09 ***
Condition (Indoor noise)	26.57	32.67	0.81	0.42
Condition (Outdoor noise)	69.50	32.67	2.13	0.04 *
Gender (M)	155.59	61.13	2.55	0.02 *

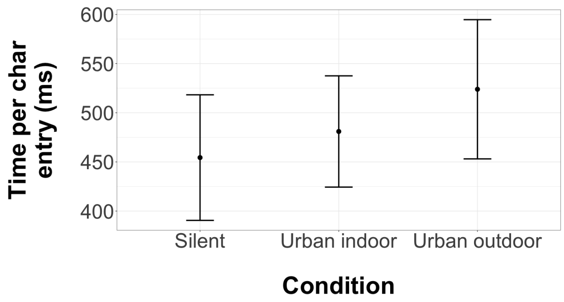


Fig. 7. Mean values for time per character entry in urban noise condition

4.3 Results: Speech Condition

4.3.1 Target Acquisition. First, we built a model to describe the time taken to tap a circle. The final model contained the Y centre coordinate of the circle and participant age as its predictors. The relationship of the Y centre coordinate was positive, indicating that the lower the circle was from the top left corner of the screen, the quicker it was to tap. For age, we see again the same trend: young participants were quicker in tapping the circles. The model was statistically significant ($\chi^2(1) = 105.39$, $p < 0.01$) describing 7.6% of variance of time taken to tap a circle ($Marginal\,R^2 = 0.08$, $Conditional\,R^2 = 0.26$).

We then built a model to describe the offset size of the touch. The final model contained only the X centre coordinate of the circle as a factor. As before, the predictor was negative, indicating that the icons were quicker to find the closer they were located to the right edge of the screen. The model was statistically significant ($\chi^2(1) = 41.85$, $p < 0.01$) and described 0.6% of the variance of the offset size ($Marginal\,R^2 = 0.006$, $Conditional\,R^2 = 0.06$).

4.3.2 Visual Search. We created a model to describe the time taken to memorise an icon. The final model contained only participant age as a predictor, again in the same direction - indicating that young participants were quicker to find the icons. The model was statistically significant ($\chi^2(6) = 12.31$, $p < 0.01$) and explained 7% of variance of time taken to memorise an icon ($Marginal\,R^2 = 0.07$, $Conditional\,R^2 = 0.17$).

Finally, we construct a model to describe the time taken to find an icon and the corresponding number of errors. However, none of the predictors sufficiently described this dependent variable.

4.3.3 Text Entry. To investigate the effect of speech condition on a typing task, we built a model describing the time needed per character entry. The model was statistically significant ($\chi^2(3) = 9.30, p < 0.03$) and described 9% of variance of time taken to type a character ($Marginal\,R^2 = 0.09$, $Conditional\,R^2 = 0.40$). Coefficients of the model are summarised in Table 7. As can been seen from Table 7, participants were significantly slower when typing a character under meaningful speech condition, compared to silent condition. We drew a boxplot to visualise the values of the mean time per character entry for each condition in Figure 8.

We then built a model describing the number of uncorrected errors in a typing task. However, none of the predictors were descriptive enough to predict the number of uncorrected errors during the typing task under the speech condition.

Table 7. Effects of model factors on predicting time per character entry in speech condition

	Estimate	**Std. Error**	t value	Pr(>|t|)
(Intercept)	396.01	47.56	8.33	1.12e-09 ***
Condition (Speech meaningful)	85.44	36.53	2.34	0.02 *
Condition (Speech meaningless)	53.09	36.76.20	1.44	0.15
Gender (M)	116.75	60.31	1.94	0.07

Significance: ‘***’ <0.001, ‘**’ <0.01, ‘*’ <0.05

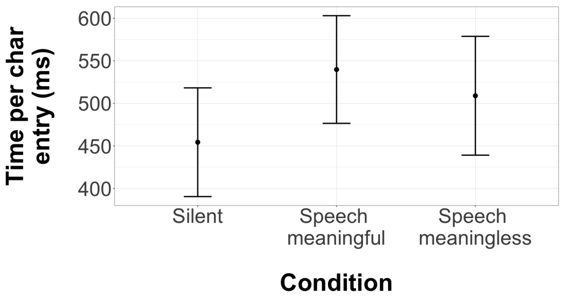


Fig. 8. Time per character entry in speech condition

4.4 Results: Interviews

The qualitative analysis presented in this section reflects on participants’ answers to the short interview session that we held after they finished the experiment. Several participants (4 out of 24) mentioned that they felt their *“overall performance was worse towards the end of the experiment”*. In contrast to this opinion, 3 out of 24 participants mentioned that their performance was better towards the end of the experiment as they were *“more used to the tasks”*.

4.4.1 Perceived Task Performance in Music Condition. Participants felt the effect of music was most prominent in the tapping task. 12 out of 24 participants claimed that they followed the tempo of the music when tapping circles. The most popular comment we received from the participants was *"I was tapping circles in rhythm with the music tempo"*. Some of the participants thought that the music improved their performance: *“Classical music improved my performance”* (P24), *“I was performing better in finding icons under both music conditions”* (P21). Interestingly, participants mentioned that in both of the music conditions they tapped on circles faster when compared to the silent condition: *“I was fast in both music conditions. But even with the slow music I was performing faster than in silence”* (P14, P20, P24). The participants also mentioned that the music made their task completion experience more enjoyable: *“Music made the task easier psychologically, I was not stressed or worried”* (P01), *“Slow music was relaxing”* (P06), *“Clicking the circles was fun with the music”* (P14), *“I was enjoying the music and focused on the task better”* (P24). Overall, interview remarks demonstrate that the participants noticed the influence of music tempo on completing target acquisition task. However, there were exclusive remarks from our participants who believed that music was annoying and distracting (P08, P10, P17) and, hence, might have deteriorated their performance: *“Slow music was annoying and distracting. I could not concentrate on finding an icon and was slower when typing a message”* (P10). However, upon checking the quantitative data we found that mean time taken to find an icon on the visual search task during the slow music condition for participants P08 (M = 1166.21 ms, SD = 257.99) and P17 (M = 1359.12 ms, SD = 462.27) was less than the mean time for all participants (M = 1753.19 ms, SD = 1166.21). Only participant P10 took longer time finding an icon under the slow music condition (M = 1860.92 ms, SD = 1098.26) compared to the total mean time for the visual search task. We also found that all three participants took less time per character entry in the text entry task (M = 431.56 ms, SD = 59.26; M = 379. 44 ms, SD = 67.38; and M = 424.65 ms, SD = 72.02 for participants P08, P10, P17 respectively) compared to the mean time of all participants (M = 485.14 ms, SD = 192.48). This shows that participants' perception does not always align with their actual performance.

4.4.2 Perceived Task Performance in Urban Noise Condition. There was a lack of consensus in the remarks regarding the urban noise condition. More than half of the participants agreed that they were annoyed and distracted with the urban outdoor noise (13 out of 24). Several participants mentioned that both urban noise conditions were distracting. Five participants complained about the outdoor urban noise condition: *"In urban outdoor noise I was stressed and alert. I had to correct the texts a lot under outdoor urban noise condition"* (P01), *"Urban outdoor noise was distracting"* (P11, P14, P19), *"I made several mistakes when finding icons in outdoor noise condition"* (P19). One participant mentioned that they performed quicker in all of the tasks during the outdoor noise as they tried to *"tune out the noise"* (P06). Meanwhile other participants complained about urban indoor noise condition: *"Ambient indoor noise was distracting, as it made feel like I was in a cafe and I felt as if I needed to be involved in a conversation with a friend"* (P06), *"Indoor noise put me almost asleep"* (P13). Surprisingly, one participant claimed that they liked the urban outdoor noise condition and it did not affect their performance: *"Traffic noise was good, I am used to it, I was quicker in tapping circles and typing tasks."* (P13). These comments are mostly in line with our quantitative findings, as our results show that participants took less time in tapping circles and memorising an icon under both indoor and outdoor urban conditions. However, time per character entry was higher for these conditions.

4.4.3 Perceived Task Performance in Speech Condition. Regarding the speech condition, 13 out of 24 participants found the speech condition to be distracting and claimed their overall task performance was worse in both of the speech conditions. The participants emphasised that speech condition deteriorated their performance particularly in visual search and text entry tasks. Some of the insights from the participants are: *"English speech was distracting. When listening to it I made more mistakes while typing"* (P13, P14, P17, P22, P23), *"I made several mistakes when finding icons in English speech condition"* (P19). Regarding the target acquisition task only a few participants felt that speech affected their performance. For example, one participant said that they were slower in tapping circles under English speech condition but could not explain the reason behind (P01). However, another participant mentioned that they tapped on circles quicker to avoid "listening to the foreign language" (P06). When we examined their data, we found that P01 did in fact take less time (M = 574.42 ms, SD = 112.69) tapping circles in English speech condition compared to the mean time of all participants (M = 592.81 ms, SD = 119.60). The quantitative data of the participant P06 is in line with their comment, as they took less time tapping circles (M = 542.75 ms, SD = 117.19) compared to the total mean time taken to tap a circle (M = 609.38, SD = 132.66). Overall, the participants claimed that the speech condition affected their performance in visual search and text entry tasks.

4.5 Summary of Results

We summarise the effects of each condition on the different dependent variables and present them in Table 8. As can been seen from the table, the target acquisition time decreased in both music conditions, as well as in both urban noise conditions. Offset size was significantly larger in the music with slow tempo condition. Further, participants spent significantly less time on memorising an icon in the urban indoor noise condition. In addition, participants produced significantly more errors in urban outdoor noise condition when searching for an icon. Finally, the time per character entry was significantly longer in the urban outdoor noise and meaningful speech conditions when compared to the silent condition.

Table 8. Table summarising the effect of ambient noise conditions on predicted variables compared to silent condition

	Music		Urban noise		Speech	
	Slow Tempo	Fast Tempo	Indoor	Outdoor	Meaningful	Meaningless
Time to tap a circle	↓ *	↓ *	↓ *	↓ *	-	-
Offset size	↑ *	↑	-	-	-	-
Time to memorise an icon	-	-	↓ *	↓	-	-
Time to find an icon	-	-	-	-		
Errors in icon search			↑	↑ *		
Time per character entry			↑	↑ *	↑ *	↑
Errors in typing	-	-				

'↓' — decreased, '↑' — increased (relative to baseline)
'*' — the effect was statistically significant, '-' — no effect was observed
Empty cells indicate a failed attempt to describe the variable with provided factors

4.6 Comparison of Cold- and Ambient Noise-Induced Situational Impairments

In this section we compare our findings to the effect of cold ambience on mobile interaction. We compare our mean values for time taken to tap a circle, offset size of the tap, time taken to memorise an icon, and the time taken to find an icon with the values presented in Sarsenbayeva *et al.* [45] and summarise them in Table 9. The comparison suggests that the effect of cold was more pronounced than all our ambient noise conditions in terms of the time taken to memorise an icon and time taken to find an icon. The effect of cold on offset size was similar for the fast tempo music, slow tempo music and meaningful speech conditions (approx. 43 pixels). In terms of time to tap a circle, the effect of cold was larger than the conditions of fast tempo music, slow tempo music, urban indoor noise, urban outdoor noise, and meaningful speech conditions, except for the meaningless speech condition. The mean values for the silent condition are slightly smaller for offset size, time to memorise an icon, and time to find an icon compared to the warm condition. Meanwhile, the time to tap a circle is approximately equal for both of the baseline conditions.

Table 9. Comparison of the effect of situational impairments against the baseline

	Baseline		Situational impairments							
Mean (SD)	**Warm**	**Silent**	**Cold**	**Music Fast**	**Music Slow**	**Urban Indoor**	**Urban Outdoor**	**Speech (Meaningful)**	**Speech (Meaningless)**
Time to tap a circle, ms	593 (137.89)	591.84 (125.07)	603 (144.62)	577.76 (135.85)	574.15 (123.45)	583.16 (117.38)	573.56 (110.39)	592.81 (119.60)	609.38 (132.66)
Offset size, px	41.34 (40.89)	39.38 (35.26)	42.66 (33.04)	42.95 (29.72)	42.11 (37.48)	41.06 (32.70)	40.91 (38.47)	42.90 (49.86)	39.47 (30.55)
Time to memorise an icon, ms	815 (150.15)	748.76 (253.89)	854 (196.47)	737.71 (233.54)	745.15 (294.29)	712.11 (194.40)	743.56 (253.03)	753.20 (319.57)	738.90 (254.39)
Time to find an icon, ms	1632.24 (1235.27)	1587.74 (871.95)	1942.46 (2750.85)	1564.70 (830.81)	1753.19 (2263.27)	1543.12 (700.54)	1633.15 (1191.98)	1637.54 (1072.61	1520.99 (767.07)

5 DISCUSSION

5.1 Effect of Ambient Noise on Smartphone Interaction

A large body of scientific work highlights the effect of ambient noise on human behaviour [22, 39], cognitive performance [5, 44, 54], and emotional state [25]. Our findings show that participants were quicker in the target acquisition task in both of the fast and slow music conditions. Our results are partly in line with the literature, as it has been shown that fast tempo music accelerates human performance in drinking [33], eating [9], or walking [34]. However, previous work has not identified a positive effect of slow tempo music on performance. In our qualitative data, participants mentioned that music in general helped them get into the rhythm of the task, which can explain why both music conditions led to a decrease in time taken to tap a circle. However, a faster completion of the task also resulted in a larger offset size. This agrees with previous work that demonstrated that while music increases the task performance speed, it also reduces overall accuracy [12]. As for the remaining tasks (visual search and text entry), we did not observe an effect of music on performance.

Another important factor to consider is that, even though literature has identified tempo as the main factor influencing human performance when listening to music [34], different types of music (*e.g.,* vocal music, rock) can also have a different effect on mobile interaction. For instance, Wen *et al.* demonstrated that performance in recall is significantly higher under classical music in contrast to rock music [55]. In our study, we manipulated the tempo of a classical music piece. While both slow and fast tempo classical music affected performance in a similar way, further research is needed to investigate the effect of a multitude of different music genres, a wider tempo range, and other musical elements such as pitch and timbre on mobile interaction.

Our results demonstrate an overall positive trend regarding the effect of urban noise on the target acquisition time and the time taken to memorise an icon. However, urban noise was negatively perceived by participants, with many participants commenting on its distracting nature. As such, there was an incentive for participants to perform quicker in these two tasks in order to reduce time spent in this unpleasant condition. However, in a real-world scenario a user would not be able to “escape” these unpleasant background noises by simply completing a task on their mobile device. Moreover, under the urban outdoor noise condition, participants made significantly more errors when finding an icon and took longer to type each character. These results are in line with the findings presented in previous work [5, 22] and show the negative effect of urban noise as reported by participants in the interviews.

The effect of speech was limited to the text entry task. Our findings show that participants took significantly longer to type a text when listening to meaningful speech. These results correspond with previous work where meaningful speech was shown to have a negative effect on cognitive performance [4, 27, 50, 54]. Participants mentioned that they were listening to the English speech (meaningful), which resulted in longer completion times when typing a text. The effect of meaningless speech was much smaller. As participants did not understand the Kazakh speech (meaningless), it was likely easier for participants to ignore the spoken text.

It is important to note that factors outside the ambient noise conditions also affected participants' performance during the tasks. For example, in the target acquisition task, the Y centre coordinate of the circle played a significant role for predicting the time to tap a circle. Furthermore, the X centre coordinate of the circle significantly affected the offset size of the tap. The offset size of touch was smaller for the targets located closer to the right edge of the screen. These findings are in line with previous work which showed that screen coordinates have a significant effect on time to tap as well as tap accuracy [20, 45]. Another common factor influencing results was age, influencing performance for time taken to tap a circle, to memorise an icon, and to find an icon. This is in line with previous work which shows that age is an important factor affecting both memory and errors during time based tasks [42].

5.2 Contrasting Situational Impairments in Mobile Interaction

In addition to ambient noise, cold ambience has been identified as a situational impairment that can affect mobile interaction. By comparing these situational impairments to each other, we were able to establish a benchmark measurement and determine what strategy should be prioritised and in which situations. To allow for a fair comparison between previously reported situational impairments, we used the same target acquisition and visual search tasks as presented in Sarsenbayeva *et al.* [45]. We then compared the results of our participants against the results obtained by those authors, in which participants were exposed to cold as a source of situational impairment.

Our results show that the mean values for time taken to tap a circle, memorise an icon and find an icon were larger in a cold environment compared to the ambient noise conditions. Cold ambience affects people physiologically [7], with a decrease in body temperature when exposed to cold — albeit at different rates per individual. As a result, the cold affects the dexterity of the fingers and leads to deteriorated fine-motor performance. Our comparison shows that the effect of ambient noise is more nuanced. Some people are more accustomed to certain types of noise than others, and the effect of these noises can be in opposite directions between people. For instance, people with a certain preference in music might be less tolerant to other types of music. These preferential differences between people cause the effect of noise to be less homogeneous than situational impairments that affect everyone similarly (cold reduces our body temperature).

Previous work has highlighted the need for accumulated knowledge in the HCI/UbiComp community [30, 31]. Liu *et al.* [31] argue that accumulated knowledge contributes to the formation of important research themes in the field. In our work we have obtained new results that are directly comparable to a previous study, and therefore allow us to benchmark mobile interaction under different situational impairments.

5.3 Detecting and Accounting for Noise-Induced Situational Impairments

Our findings demonstrate that mobile interaction can be affected by ambient noise in certain situations. Previous work has argued that detecting situational impairments is a fundamental step towards the successful adaptation of mobile interfaces [46]. The automatic detection of situational impairments during mobile interaction opens the way to appropriate interface adaptations; thus, enabling the interaction with mobile devices to be more appropriate to the user's context. Furthermore, solutions should ideally leverage the built-in sensors of the mobile device [47] as opposed to requiring additional instrumentation (*e.g.,* external temperature and humidity sensors to receive climatic parameters [1]). Following this suggestion, we argue that the built-in microphone of mobile devices can be used to detect noise-induced situational impairments, as previously suggested by Kanjo *et al.* [27]. In addition, a classifier could be used to distinguish between different noise types, as our results show that they can have different effects. Smartphone interfaces would then accommodate accordingly based on the condition detected. For example, if exposure to urban noise or speech is detected (shown to adversely affect text entry) while a user is typing, the phone can present an alternative interface to mitigate the effect of potential noise-induced situational impairments (*e.g., "WalkType"* interface by Goel *et al.* [14], *"Fat thumb"* technique by Boring *et al.* [8]).

5.4 Limitations

Our study had several limitations. First, the study settings were strictly controlled. It is possible that in a naturalistic environment ambient noise types would be more diverse, and multiple noise types could occur simultaneously (*e.g.,* urban outdoor noise might contain music in a touristic part of the city). However, controlling for individual noise types was necessary as our goal was to systematically compare the effect of specific ambient noises on performance. Second, we were limited in the number of sounds included and did not include other types of music (*e.g.,* varying music genres, music with lyrics), urban noise (*e.g.,* markets, public performances), or speech (*e.g.,* second language of the participant). These are potential research directions that can be explored in future studies. We also did not run our study under different volume levels, but kept the noise level constant at between 55-60 dB to avoid participant discomfort.

Finally, we restricted our participants to use only their index finger to interact with the smartphone. We argue that this restriction was necessary to draw a fair comparison between the effect of ambient noise and cold ambience [45]. Moreover, by restricting the interaction technique we created a more comparable setting between participants.

6 CONCLUSION

In this study we investigate the effect of ambient noise on mobile interaction performance in target acquisition, visual search, and text entry tasks. We found that participants were significantly quicker in completing the target acquisition task in music conditions (both fast and slow) compared to the silent condition. However, they were significantly less accurate while listening to slow music. During the visual search task, participants took significantly less time to memorise an icon while listening to urban noise, but made more errors when finding an icon under urban outdoor noise. Participant performance during the text entry task was significantly affected by the urban outdoor noise and meaningful speech conditions. The comparison of cold-induced and noise-induced situational impairments on mobile interaction showed that the effect of cold ambience was more prominent on tasks requiring fine-motor movements, whereas the effect of ambient noise was more prominent on tasks requiring cognitive skills. Our findings enhance the understanding of noise-induced situational impairments on mobile interaction and contribute towards accumulating knowledge in situational impairments research. Furthermore, detection of ambient noise and noise-induced situational impairments may be used for sensing user context and adapting the interface accordingly to mitigate their effect on mobile interaction.

ACKNOWLEDGMENTS

This work is partially funded by the Academy of Finland (Grants 285459-iSCIENCE), the European Commission (Grant 6AIKA-A71143-AKAI), and Marie Skłodowska-Curie Actions (645706-GRAGE).

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Received February 2018; revised April 2018; accepted April 2018

Chapter 5

Quantifying the Effects of Stress on Mobile Interaction

In this chapter we quantify the effect of an internal contextual factor – stress – on mobile interaction. Stress is defined as a mental state often experienced on a regular basis that has been shown to negatively influence people's everyday activities [104, 126, 205]. As the nature of some stressors is temporal [145, 251] and caused by a specific situation (*e.g.,* work related, family related) [128], in this work we study the effects of stress on mobile interaction from the perspective of SIIDs. Despite the acknowledged negative effects of stress on human cognitive performance (*e.g.,* impaired working [146,281] and declarative memory [122,178]), its' effect on mobile interaction has yet to be explored.

We induce stress on our participants using the *Trier Social Stress Test* [121] – a protocol commonly used in Psychology research to induce stress. Stress was induced in two steps: first, the participants delivered a five-minute speech explaining why they are the best candidate for their dream job. Then the participants had to perform consecutive mathematical subtraction. Both of the tasks were performed in front of the panel of judges composed by our research confederates. We asked our participants to complete smartphone tasks upon their arrival (baseline measurements) and under the induced stress. We validated the occurrence of stress using HRV data, derived from physiological data collected with an Empatica E4 [57] wearable sensor. In addition, we also used State-Trait Anxiety Inventory [250] self-report questionnaire to validate the presence of stress in participants.

Our findings show that stress significantly affected participants' performance in the target acquisition and visual search tasks; however, our results did not provide any evidence on the effect of stress on the text entry task. Precisely, our participants took significantly less time to complete the tap on the targets when they were stressed.

Moreover, their tapping accuracy was significantly lower when they were stressed as compared to the baseline condition. Regarding, the visual search task, our results indicate that participants were significantly faster to memorise icons when they were stressed. These findings are in line with prior research showing that people rush to complete the tasks to "escape" the anxiety and discomfort caused by stress [163].

The results of this study enhance our understanding of the effects of stress on mobile interaction and contribute to accumulation of knowledge on the SIIDs research. The details of our approach can be found in the attached publication in Section 5.1.

5.1 Publication

Zhanna Sarsenbayeva, Niels van Berkel, Danula Hettiachchi, Weiwei Jiang, Tilman Dingler, Eduardo Velloso, Vassilis Kostakos, and Jorge Goncalves. 2019. Measuring the Effects of Stress on Mobile Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 3*, 1, Article 24 (March 2019), 18 pages. DOI: `https://doi.org/10.1145/3314411`.

Ethics ID: 1851997.1, The University of Melbourne Human Ethics Advisory Group.

Measuring the Effects of Stress on Mobile Interaction

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Research shows that environmental factors such as ambient noise and cold ambience can render users situationally impaired, adversely affecting interaction with mobile devices. However, an internal factor which is known to negatively impact cognitive abilities – stress – has not been systematically investigated in terms of its impact on mobile interaction. In this paper, we report a study where we use the Trier Social Stress Test to induce stress on participants, and investigate its effect on three aspects of mobile interaction: target acquisition, visual search, and text entry. We find that stress reduces completion time and accuracy during target acquisition tasks, as well as completion time during visual search tasks. Finally, we are able to directly contrast the magnitude of these effects to previously published effects of environmentally-caused impairments. Our work contributes to the growing body of literature on situational impairments.

CCS Concepts: • **Human-centered computing** → Empirical studies in HCI; • **Human-centered computing** → Ubiquitous and mobile computing; Smartphones.

Additional Key Words and Phrases: Smartphones, situational impairments, mobile interaction, stress, performance, Trier Social Stress Test

ACM Reference Format:
Zhanna Sarsenbayeva, Niels van Berkel, Danula Hettiachchi, Weiwei Jiang, Tilman Dingler, Eduardo Velloso, Vassilis Kostakos, and Jorge Goncalves. 2019. Measuring the Effects of Stress on Mobile Interaction. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3, 1, Article 24 (March 2019), 18 pages. https://doi.org/10.1145/3314411

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2474-9567/2019/3-ART24 $15.00
https://doi.org/10.1145/3314411

1 INTRODUCTION

Due to the ubiquitous nature of smartphones, users interact with them under varying environmental (*e.g.,* in noisy environments) and internal (*e.g.,* under stress, in different moods) conditions. Previous research has shown that environmental and contextual factors, such as cold ambience [12], ambient noise [44], encumbrance [38], and walking [11] negatively affect mobile interaction and lead to *situational impairments*. This has given rise to a growing body of work in HCI that aims to enable smartphones to detect when the user is situationally impaired and subsequently adapt the interface to mitigate the effects of such impairments during mobile interaction [43, 46, 57].

Although prior research has emphasised the importance of understanding the effects of situational impairments [43, 49, 63], these studies mostly focus on environmental factors, such as cold ambience. In contrast, relatively little work has investigated the effect of an important internal factor on mobile interaction: *stress*, a mental state often experienced on a daily basis [1], which has been shown to negatively impact performance in everyday activities (*e.g.,* [16, 22, 39]).

In this paper, we investigate the effect of stress on task performance in smartphones. According to Lazarus *et al.* [23], stress can be defined in terms of the relationship between an individual and an environment or situation [51]. Given this notion [23] and the temporal effect of certain stressors (personal or work-related) on human behaviour [26, 55], stress has been identified as a potential cause of situational impairment that is likely to have an impact during mobile interaction [43].

In our study, we use the *Trier Social Stress Test* (TSST) [20] to induce stress in our participants in order to measure its effect on three mobile interaction tasks: target acquisition, visual search, and text entry [44]. We show that stress significantly reduces target access time and accuracy during target acquisition tasks compared to the baseline, as well as completion time during visual search tasks. Further, we directly contrast the magnitude of stress-induced situational impairments to other situational impairments based on results in the literature, namely cold ambience [42] and ambient noise [44].

The main contributions of this paper are to quantify the effect of stress on mobile task performance, compare its effect size to that of cold- and noise-induced situational impairments, and, hence, to contribute to the growing body of research on situational impairments.

2 RELATED WORK

Previous work has highlighted that different environmental and contextual factors, such as cold ambience [12], ambient noise [44], mobile state of the user [11], and encumbrance [38] can negatively affect mobile interaction. These factors can cause users to experience situational impairments and, thereby, impact their performance during mobile interaction [43]. For example, cold ambient temperature has been shown to adversely affect smartphone input performance [12, 42]. In particular, throughput and accuracy drop significantly when performing acquisition tasks under cold temperatures. Other studies have shown a negative effect of walking on text entry [11, 35] and target acquisition tasks [48]. User encumbrance also negatively affects mobile interaction, resulting in decreased accuracy, longer target acquisition times, and increased error rate [38].

Sarsenbayeva *et al.* [44] measured the effect of background noise on smartphone interaction performance. The types of background noise presented in that study included music with fast and slow tempo, urban indoor and outdoor noise, and meaningful and meaningless speech. Similar to our study, mobile input performance was measured in terms of three common smartphone activities: target acquisition, visual search, and text entry. Performance under ambient noise conditions was benchmarked against the silent condition. The authors found that music reduced completion time during target acquisition tasks, while urban noise and speech increased the text entry rate. Although a number of previous studies have investigated the effect of stress on interaction with stationary technology (*e.g.,* keyboard and mouse), the effect of stress on mobile interaction remains under-explored. For example, Karunaratne *et al.* [18] reported stronger keyboard taps amongst participants exposed to stressful conditions. Furthermore, Rodrigues *et al.* [40] investigated the effect of stress on mouse movements. The authors found that stressed students, when presented with challenging questions, carried out significantly more mouse movements [40].

In our study, we contribute to the growing body of research on situational impairments [43] by quantifying the effect of stress on interaction with smartphones, an internal factor that has been shown to adversely impact performance when using other technologies, such as desktop computers [18, 40, 62]. We achieve this by using the TSST protocol [20] to induce stress in our participants, and measure changes to their performance while completing typical smartphone tasks.

2.1 Cognitive and Physiological Effects of Stress

Behavioural and psychological scientists study the effect of stress on humans' daily lives for a variety of reasons. For example, researchers have aimed to identify the events leading to stress and how negative outcomes of cumulative stress can be avoided [14].

Early work, showed a curvilinear relationship between arousal and task performance, particularly with very high and very low levels of arousal inhibiting task performance, whereas moderate levels facilitate it [65]. More recently, research has shown the negative effect of stress on human cognitive performance [67]. For example, stress negatively affects working memory [27, 67] and verbal declarative memory [21, 37]. In addition, studies by Payne *et al.* [39] and Jelici *et al.* [16] report adverse effects of stress on human cognition resulting in memory impairments. Lupien *et al.* [26] also show that under stressful conditions, declarative memory is significantly impaired compared to a non-stressful condition in a word-pairs recall task. Moreover, Kuhlmann *et al.* [22] show that acute stress significantly delays memory retrieval. They utilise the TSST, a widely used protocol for inducing stress in participants through two tasks: public speaking and arithmetic subtraction [20]. They then asked their participants to recall pairs of words memorised at the beginning of the experiment. The results of this study show that stressed participants have significantly reduced memory retrieval as compared to the control condition [22]. Wolkowitz *et al.* [64] report similar results showing that stress has a detrimental effect when recalling words from a previously learnt list.

Further, Marquart [29] observed that stress decreased participants' learning ability and results in non-adaptive behaviour (*e.g.,* longer reaction time when completing cognitive tasks [23]). Verville *et al.* [61] found that participants who were exposed to a stressful condition required significantly longer time for recognising pictures that were flashed on a screen as compared to a control group. This, however, is a contested finding as other studies have shown that stress sped up participants' performance during an image sorting task (*e.g.,* [33]). In addition, a reduction of task completion time resulted in a greater number of errors [33]. These results are similar to a study by McKinney [32], where stress increased the number of errors in completing multiplication problems and a learning syllables task.

Based on this rich literature we hypothesise that stress will hinder user performance in smartphone tasks. In particular, participants under stress will be less accurate when compared to a baseline measurement.

2.2 Stress Detection Methods

Stress induces biological responses, which can thus be physiologically measured. Examples include changes in skin conductivity [50], heart rate variability [56], muscle tension [56], and heart rate [47]. Several studies have focused on the development of wearable technology that allows for the unobtrusive tracking of physiological measures. As a result, a variety of wearables exists that track physiological measures (*e.g.,* Empatica E4 wristband[1], Oura ring[2]).

[1]https://www.empatica.com/research/e4/
[2]https://ouraring.com/

Several studies have attempted to detect stress from people's interaction behaviour using sensor-based technologies [3, 14, 41]. For example, Hernandez *et al.* use a pressure-sensitive keyboard and a capacitive mouse to detect the effect of stress during computer interaction. They found that more than half of their participants increased their typing pressure under the stressful condition when compared to the control condition. They also showed that the majority of participants (75%) covered more of the surface of the mouse when they were stressed [14]. Furthermore, Exposito *et al.* [10] suggest using iPhone's built-in keyboard pressure sensor to detect stress. The authors show that under stressed conditions, participants typing pressure was higher when compared to non-stressed conditions [10]. Prior research has also shown that the combination of wearable sensors and smartphone interaction patterns can detect stress more accurately. For instance, Sano and Picard [41] achieved a higher accuracy rate for stress detection (75%) compared to previous results (53%) that only used smartphone interaction patterns [3]. Other stress detection methods are based on self-reports and questionnaires. For example, Cohen *et al.* [9] suggest the use of perceived stress as an objective stress measure. Further, Spielberger and colleagues recommend asking participants to self-report their anxiety levels using the State-Trait Anxiety Inventory (STAI) to identify the occurrence of stress [54].

In our study, we collect both sensor and self-report data to validate that we are indeed inducing stress in our participants throughout the experiment. Namely, we use heart rate variability (HRV) derived from the data of an Empatica E4 and collect self-report data using the STAI questionnaire.

3 METHOD

In this study, we investigate the effect of stress on performance on three common mobile interaction tasks: target acquisition, visual search, and text entry. We use the experimental tasks developed in the study by Sarsenbayeva *et al.* [44]. This allows us to directly compare the effects of stress-induced situational impairments with those previously reported for cold-induced and noise-induced situational impairments. We describe each task in detail below.

3.1 Smartphone Tasks

We used a Samsung Galaxy S7 smartphone (Android 7.0) with a 5.1-inch screen (1080×1920px) in this experiment. This smartphone model was chosen in order to have an identical screen size and screen resolution to the smartphone used in previous studies by Sarsenbayeva *et al.* [42, 44] on situational impairments. The three tasks were presented to participants in a random order to avoid sequence effects. Participants first completed extensive training until they were comfortable with each of the presented tasks, thus minimising any potential learning effects. Both the training and actual tasks were completed while standing, and participants were instructed to use only the index finger of their dominant hand for interaction, while holding the smartphone with their non-dominant hand.

3.1.1 Target Acquisition Task. In the target acquisition task participants are asked to tap circular targets (radius = 135 px) which appear one at a time at random locations on the screen. Each circle has an indicated centre and participants are asked to tap the indicated center of the targets as precisely and quickly as possible. We log the coordinates of the target's centre, the participant's touch point, and the elapsed time. The interface of the task is shown in Figure 1-A.

3.1.2 Visual Search Task. In the visual search task, participants must find a target icon amongst 24 other icons (100×100 px), arranged according to a 4×6 grid [13]. The target icon is first shown, participants can then take as much time as needed to memorise it (Figure 1-B). In the subsequent screen they must find and tap the memorised target among 24 icons (Figure 1-C). To minimise any potential learning effects, the application ensures that the target is randomly selected and remaining icons are randomly distributed across the grid.

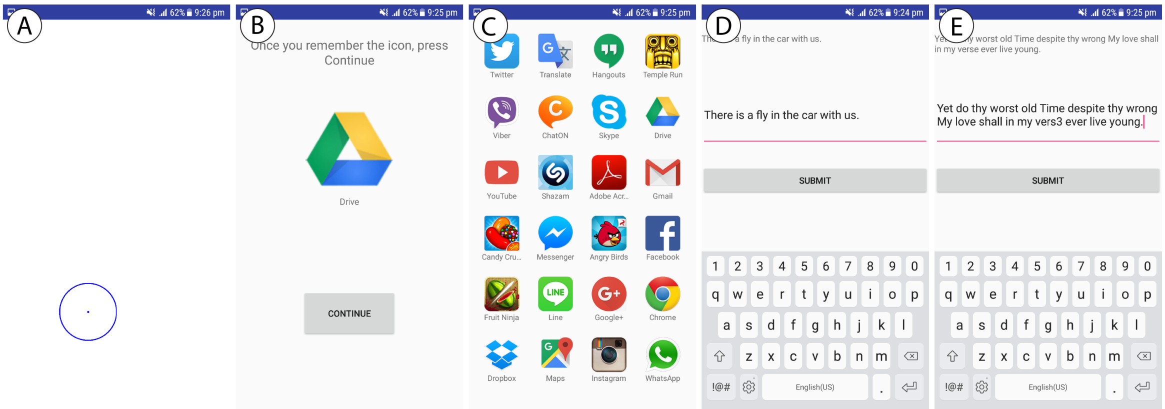

Fig. 1. Interface of the application with Target Acquisition Task (A), Visual Search Task (B-C), and Text Entry Task with user's input for easy and difficult texts (D-E).

3.1.3 Text Entry Task. In the text entry task, our participants are presented with a snippet of text (displayed on the top-half of the screen), which they must re-type in a text box. The texts are of varying difficulty: 1) easy – consisting of only one sentence with common words widely used on a daily basis (see Figure 1-D), 2) difficult – consisting of several sentences chosen from Shakespeare's sonnets (see Figure 1-E). In total we have 10 easy sentences and 10 difficult sentences, and at each round of tasks a sentence is randomly selected by the application. We validated the difficulty of the sentences with the Flesch-Kincaid readability test [19]. Easy sentences had an average grade of 1.6 and difficult sentences had an average grade of 5.1.

3.2 Participants

We recruited 24 participants between 20 and 55 ($M = 31, SD = 9.5$) years old through our university's mailing lists and snowball recruitment with equal number of male and female participants to avoid gender bias [59]. Participants had a diverse range of educational backgrounds (*e.g.*, Electrical, Mechanical, Infrastructure and Civil Engineering, Agriculture, Entomology, Architecture, and Computer Science).

3.3 Procedure

To induce stress in our participants, we followed the TSST protocol [20]. TSST is a validated protocol used to induce stress in study participants that has been widely used in Psychology research. The original TSST protocol [20] describes three main stress points in the experiment: following a relaxation period (20 minutes), following stress-inducing tasks (speech and arithmetic), and following post-stress recovery. Hence, we ask participants to complete the smartphone tasks at these three points. The overview of the experimental procedure is presented in Figure 2.

In order to validate whether our participants experienced stress throughout the experiment, we calculated their heart rate variability (HRV) from the Empatica E4 wristband data, as HRV has been shown to correlate with a person's stress levels [56]. We also collected self-reported anxiety levels of the participants via the STAI questionnaire [54], a tool commonly used by researchers conducting studies with the TSST to validate fluctuations in stress levels. Sensor data was then cross-referenced with smartphone data using timestamps.

In line with the TSST protocol, participants were not aware that the study investigated the effect of stress on mobile interaction, and were not informed that we would induce stress on them to avoid triggering anxiety-related

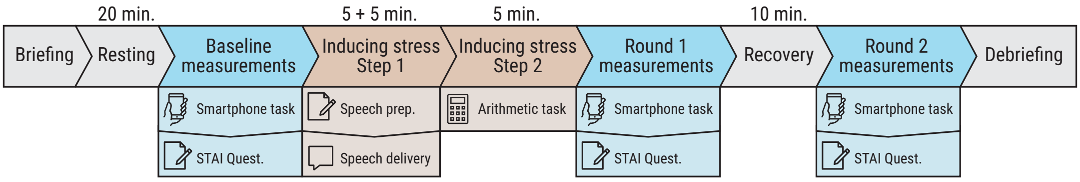

Fig. 2. Experimental Procedure.

behaviours. Again, according to the TSST protocol, this is done to reduce participant bias and to let us observe the natural reaction of participants to stress. The experimental design was approved by the Ethics Committee of our university. The experiment duration was approximately 90 minutes per participant, including briefing, training, data collection, and final interview. Each participant received a $30 gift voucher for participation.

3.3.1 Participant Briefing. The experiment took place at our institution's usability lab, with an experimental setup consisting of two adjacent rooms, as recommended by the TSST protocol. One room works as a desensitisation room, where participants can rest and relax, while the other room is used for the stress-inducing tasks. Upon arrival, we welcomed our participants to the desensitisation room. We then informed them that we are investigating their cognitive performance as measured by their presentation skills and arithmetic skills, as well as their performance in a range of smartphone tasks. We then asked participants to sign a consent form agreeing to participate in the study and collected their demographic data (age, gender, background, dominant hand). Next, we instrumented our participants with an Empatica E4 wristband, and instructed them to wear it throughout the experiment on their non-dominant hand. Following this setup we asked our participants to complete all smartphone tasks for training purposes. Participants trained with all three study tasks in random order until they were comfortable with each one.

3.3.2 Baseline Measurements. After training, participants were left alone for 20 minutes, so that they could rest and stabilise. During this period we provided them with reading material with neutral content to keep them occupied and not cause any anxiety (descriptions and photographs of plants growing in different regions of the world), as recommended in the TSST protocol [20]. We also asked them not to use their smartphone during this time. Following, the participants were asked to complete a round of tasks on a smartphone. The purpose of this stage was to create a baseline measurement of performance while not stressed. After finishing the tasks, the participants completed the STAI questionnaire [54] to measure their perceived anxiety state.

3.3.3 Inducing Stress — Step 1. We guided our participants to the experiment room. Here, we provided them with a scenario according to which they were applying for their dream job and needed to attend a hiring interview. Participants were given 5 minutes to prepare a speech to convince a panel as to why they were the best candidate for their dream job. We also informed them that their performance was going to be video-recorded and reviewed by judges trained in public speaking. Once the preparation time was over, the participants were asked to deliver their speech in front of the panel of three judges, who were, unbeknownst to the participants, confederates of the research team. Participants had to speak for the entire 5 minutes, during which the panel members did not give any feedback and maintained neutral facial expressions.

3.3.4 Inducing Stress — Step 2. Upon completing step 1, participants were asked to perform an arithmetic task. We asked them to subsequently decrement 1022 by 13 and to say the number sequence out loud. The task is inspired by the 'Serial Sevens' tasks [52], which is used in clinical tests to assess mental functions, and lasts for 5 minutes. In case of miscalculation, a researcher informed the participants of their error and they were asked to restart the task from 1022. The purpose of the arithmetic task was to induce further stress on participants.

After completing the arithmetic task, the participants completed a round of tasks on a smartphone under stress, followed by the STAI questionnaire (Round 1).

3.3.5 Post-Stress Recovery. At this stage, we brought participants back to the desensitisation room and left them alone for 10 minutes to rest and recover. We then asked them to complete a final round of smartphone tasks and complete the STAI questionnaire (Round 2). According to the TSST protocol [20], cortisol level reaches its peak during this moment of the experiment and, therefore, we wanted to assess their performance during mobile interaction at this point.

3.3.6 Participant Debriefing. Finally, we debriefed participants about the real purpose of the study and explained that it was expected to experience stress during the experiment. Further, we clarified that the tasks performed during the experiment were unreasonably difficult and did not reflect upon their aptitude or ability. We also informed them that we did not video-record their performance. We then conducted a short, semi-structured interview with our participants, asking them to report on their subjective perception of the experiment and the effect of stress on their performance.

4 RESULTS

In this section, we report our results regarding the effect of stress on our participants' performance across target acquisition, visual search, and text entry tasks. We also report participants' subjective assessments of their performance in the aforementioned smartphone tasks.

4.1 Validation of Stress Occurrence

We used HRV to validate the presence of stress in our participants and followed the process, described by McDuff and colleagues [31]. To generate HRV data from the bio-signals collected with the Empatica E4 sensor, we performed the generic HRV analysis method as follows. First, we interpolated and re-sampled inter-beat interval (IBI) data at $4Hz$, to align the signals in a uniform time interval. Then we obtained an HRV power spectrum in time series from the detrended interpolated IBI data, by applying the Fast Fourier Transform (FFT) algorithm with a 512-sized slide window (*i.e.,* a 512-sample or 128-second segment of a signal). We calculated the HF (High-Frequency) powers of the HRV as the summation of the discrete points corresponding to the power spectrum under $0.15 - 0.40Hz$. As HF HRV was previously shown to be a reliable indicator of stress occurrence [4], we used it for further validation of presence of stress in our participants. We acknowledge that HRV can be a result of multiple factors apart from stress; however, we argue that in combination with the established stress-inducing protocol and participants' self-reports, we were able to reliably validate the occurrence of stress during our experiment. In addition, we did not collect EDA data due to the following reasons. First, EDA data collected from the wrist is shown to describe thermoregulatory relevant electrodermal phenomena, rather than the psychophysiological nature of the response [8]. Second, EDA is better suited for validating stress caused by discrete events (*e.g.,* electrical shock) [7, 8, 51], whereas in our study participants experienced longitudinal cumulative stress.

We applied a one-way repeated measures ANOVA, which yielded a statistically significant effect of stress on heart rate variability ($F(2, 24) = 6.54, p < 0.01$). A Tukey HSD post-hoc comparison test (with Bonferroni corrections) reveals that HRV values during Stress Induction ($M = 32.84, SD = 20.89$) and Post-stress Recovery periods ($M = 37.24, SD = 18.69$) are significantly lower ($p < 0.01$) compared to HRV values during the baseline measurements ($M = 40.81, SD = 26.05$). Since low values of HF HRV indicate a physiological presence of stress [15], we can conclude from the HRV results that the participants were stressed after undergoing both the speech and arithmetic subtraction tasks of the protocol. The mean values for HF HRV are visualised in Figure 3.

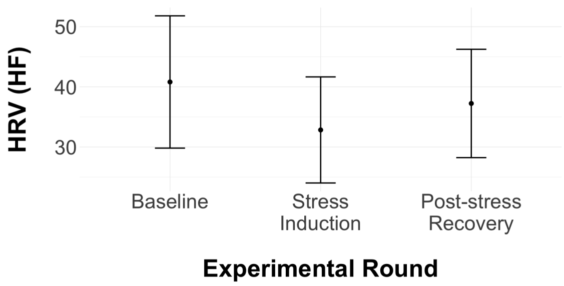

Fig. 3. HRV (HF) Mean Values (95% Confidence Interval (CI))

Next, we examined participants' self-reported anxiety values as measured by the STAI questionnaire as collected following completion of each round of smartphone tasks. A one-way repeated measures ANOVA yielded a statistically significant effect of stress on self-reported anxiety values ($F(2, 24) = 10.23, p < 0.01$). Post-hoc comparisons using the Tukey HSD test (with Bonferroni corrections) indicated that participants were significantly more anxious ($p < 0.01$) during Stress Induction period ($M = 37.08, SD = 11.77$) of the experiment compared to the baseline values ($M = 30.71, SD = 6.37$). Furthermore, participants reported feeling significantly less anxious ($p < 0.01$) during Post-stress Recovery period ($M = 31.79, SD = 8.64$) when compared to Stress Induction period. The mean values for self-reported anxiety levels are presented in Figure 4.

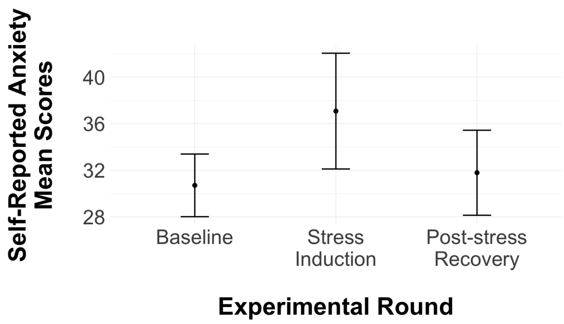

Fig. 4. Self-Reported Anxiety Mean Values (95% CI)

From the sensor data and self-reported anxiety values we can conclude that the study protocol performed as intended in terms of inducing stress in participants.

4.2 Target Acquisition Task

We measured the target acquisition performance in terms of target acquisition time (ms), offset (px) between the target centre and the touch point, and effective throughput[3]. First, we applied a one-way repeated measures ANOVA to investigate the effect of stress on target acquisition time. The result showed a statistically significant

[3]A measure of human performance in completing target selection tasks that describes the relationship between the difficulty of the task and target acquisition time [28]

effect of stress on time taken to hit a target ($F(2, 24) = 17.05, p < 0.01$). Post-hoc comparisons using the Tukey HSD test (with Bonferroni corrections) indicate that participants take significantly less time to tap a circle in Stress Induction ($M = 534.77, SD = 124.43, p < 0.01$) and Post-stress recovery periods ($M = 520.18, SD = 126.52, p < 0.01$) as compared to the baseline ($M = 538.68, SD = 127.58$). However, we found no statistically significant difference between time taken to hit a circle between Stress Induction and Post-stress Recovery periods. Mean target acquisition time values are presented in Figure 5.

Fig. 5. Mean Target Acquisition Time (95% CI)

Then, we investigated the effect of stress on the touch accuracy during target acquisition. A one-way repeated measures ANOVA showed a statistically significant effect of stress on the offset size ($F(2, 24) = 20.11, p < 0.01$). Post-hoc comparisons using the Tukey HSD test (with Bonferroni corrections) indicate that touch offset size is significantly larger in Stress Induction ($M = 49.14, SD = 25.94, p < 0.01$) and Post-stress Recovery periods ($M = 50.20, SD = 26.51, p < 0.01$) as compared to the Baseline value of the offset size ($M = 46.47, SD = 25.57$). However, we found no statistically significant difference in offset size between Stress induction and Post-stress Recovery measurements ($p > 0.05$). Mean offset size values are visualised in Figure 6.

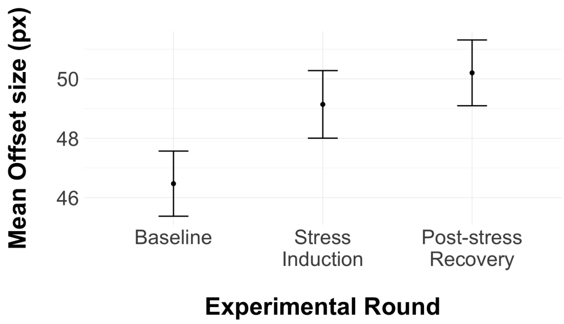

Fig. 6. Mean Offset Size (95% CI)

Finally, we studied the effect of stress on effective throughput. Effective throughput was calculated as suggested by Soukoreff and MacKenzie [53]. A one-way repeated measures ANOVA did not show a statistically significant effect of stress on the effective throughput during target acquisition tasks ($p > 0.05$).

4.3 Visual Search Task

We measured the performance during the visual search task in terms of the time taken to memorise the target icon, and the time taken to find the target icon. A one-way repeated measures ANOVA showed a statistically significant effect of stress on the time taken to memorise an icon ($F(2, 24) = 31.77, p < 0.01$). Post-hoc comparisons using the Tukey HSD test (with Bonferroni corrections) indicated that participants take less time to memorise an icon in Stress Induction ($M = 714.52, SD = 229.27, p < 0.01$) and Post-stress Recovery periods ($M = 702.31, SD = 200.85, p < 0.01$) when compared to the baseline measurement ($M = 800.51, SD = 331.15$). However, we found no statistically significant difference in the time taken to memorise an icon between the values measured during Stress Induction and Post-stress Recovery ($p > 0.05$). Mean values for time taken to memorise an icon are visualised in Figure 7.

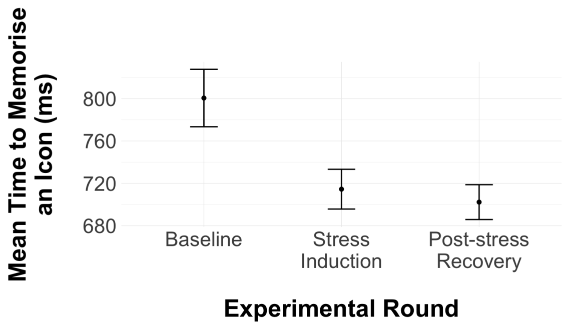

Fig. 7. Mean Time to Memorise an Icon (95% CI)

Then, we conducted a one-way repeated measures ANOVA to investigate the effect of stress on time taken to find a target. The results of the test did not show a statistically significant effect of stress on visual search time ($p > 0.05$). Finally, we investigated the effect of stress on the number of errors during visual search tasks. A one-way repeated measures ANOVA did not show an effect of stress on the number of errors.

4.4 Text Entry Task

We measured text entry performance in terms of character entry rate, number of total errors, and total error rate as suggested by Soukoreff and MacKenzie [53]. Character entry rate was calculated as the time taken to enter a character, while number of total errors was calculated as the sum of uncorrected and corrected errors. Finally, total error rate was the ratio between the number of total errors and total entered characters. We conducted a one-way repeated measures ANOVA to investigate the effect of stress on time per character entry. The results did not reveal a statistically significant effect of stress on time per character entry ($p = 0.056$), with participants tending to take less time per character entry after post-stress recovery time. Furthermore, a one-way repeated measures ANOVA did not show a statistically significant effect of stress on the number of total errors ($p > 0.05$), nor on total error rate ($p > 0.05$).

As we presented our participants with two types of texts: easy and difficult, we conducted a two-way repeated measures ANOVA, accounting for the effect of difficulty and stress on the number of total errors and total error rate. We did not consider this difference for the character entry rate, as this is already accounted for with text difficulty. The results of the ANOVA showed a statistically significant effect of the difficulty of the text on the number of total errors ($F(1, 24) = 34.22, p < 0.01$). However, we did not find an interaction effect between the difficulty of the text and stress ($p > 0.05$). Finally, a two-way repeated measures ANOVA did not show a statistically significant effect of the difficulty of the text on the total error rate ($p > 0.01$).

4.5 Interviews

To familiarise ourselves with the data collected during the semi-structured interviews, we read through each response and analysed it using the following process. One researcher printed participant responses and completed initial coding, utilising a data-driven approach based on our aforementioned results. Then, three researchers compared the initial codes and merged these according to their similarity (*e.g., "I rushed the task"* and *"I got progressively slower"* merged to *"Task completion time"*). The three researchers then independently coded participants' responses for each question as based on the initial codebook. We reviewed the final coding to identify similarities that allowed thematic grouping. The main themes are described below.

4.5.1 Psychological Effects of Stress on Perceived Performance. The majority of the participants ($N = 19$) stated that stress affected their behaviour. For instance, participants ended up rushing through the tasks when stressed. Rushing the tasks affected their performance in terms of accuracy during target acquisition tasks. Example quotes are: *"I was more annoyed and just wanted to get the tasks done, so I rushed"* (P13), *"I think because I rushed the task I got less accurate"* (P17), *"When I'm stressed I get adrenaline, and tap faster, but when I make a mistake I go slower, but still not very accurate"* (P14). These findings are in line with our quantitative data, that showed that participants took significantly less time to tap circles when they were stressed as well as they were less accurate.

Participants also reported that stress had an effect on their ability to concentrate and focus. However, the comments regarding concentration were not unanimous. While some participants ($N = 8$) claimed that stress impaired their concentration, others claimed that stress sharpened their focus ($N = 5$). This concords with the fact that, for some participants their perceived performance during visual search and text entry tasks was improved, for example, *"I felt I messed up during first few trials as I wasn't paying attention, but stress made me focus better"* (P07), *"After speech I couldn't concentrate"* (P20). While for others, their perceived performance deteriorated: *"I forgot the icons as I was stressed"* (P04), *"I was thinking about the icons, focused on them, but after the arithmetic task I wasn't focused on the icon, and 60% of the time i just pressed continue and was thinking what was the icon I needed to find"* (P17), *"After presentation I couldn't focus, when I was doing the icons task I was thinking about my presentation and it took longer time to focus on the icon"* (P18).

4.5.2 Physical Effect of Stress on Perceived Performance. We found that stress affected participants not only psychologically, but also physically. Several participants ($N = 5$) claimed that stress had a physical effect on them. All of these participants reported that they felt jittery under stress, and as a result they were less accurate when completing target acquisition tasks. We recorded the following quotes from our participants: *"I was more jittery after the speech, my fingers were more shaky"* (P09), *"My fingers were shivering, especially after the presentation. My head was cloudy, and I was not focused"* (P14). These findings are in line with our quantitative results, which show that participants are less accurate in target acquisition task when they are stressed.

4.5.3 Self-Reflection. We also found that several participants reflected on their performance in the speech and arithmetic tasks. This self-reflection was mostly performed during the final part of the study when participants were left alone in the desensitisation room for a post-stress recovery period. While some participants ($N = 7$) expressed their concerns regarding their performance during the arithmetic task: *"I was thinking that I could have done better in the arithmetic task"*, others ($N = 7$) reflected on their performance during the speech task: *"I was thinking how bad I did in the presentation"* (P16). These comments indicate that even after the stress-inducing tasks during post-stress recovery period, participants were still preoccupied with their performance.

Table 1. Comparison of the Effects of Situational Impairments against Respective Baseline.

	Baseline			Situational Impairments								
	Warm	**Silent**	**No stress**	**Cold**	**Music Fast**	**Music Slow**	**Noise Indoor**	**Noise Outdoor**	**Speech Meaningful**	**Speech Meaningless**	**Stress**	**Post-Stress Recovery**
Time to tap a circle, ms	593.00	591.84	538.68	603.00 + 1.7%	577.76 - 2.4%	574.15 - 3.0%	583.56 - 1.4%	573.56 - 3.1%	592.81 + 0.2%	609.38 + 3.0%	534.77 - 0.7%	520.18 - 3.4%
Offset size, px	41.34	39.38	46.47	42.66 + 3.1%	42.95 +9.1%	42.11 + 6.9%	41.06 + 4.3%	40.91 + 3.9%	42.90 + 8.9%	39.47 + 0.3%	49.14 + 5.7%	50.20 + 8.0%
Time to memorise an icon, ms	815.00	748.76	800.51	854.00 + 4.8%	737.71 - 1.5%	745.15 - 0.5%	712.11 - 4.9%	743.56 - 0.7%	753.20 + 0.6%	738.90 - 1.3%	714.52 - 4.6%	702.31 - 12.3%
Time to find an icon, ms	1632.24	1587.74	1602.45	1942.46 + 19.0%	1564.70 - 1.4%	1753.19 + 10.4%	1543.12 - 2.8%	1633.15 + 2.9%	1637.54 + 3.1%	1520.99 - 4.2%	1496.50 - 6.6%	1506.38 - 6.0%
Character entry rate, ms/char	n/a	454.39	560.88	n/a	488.11 + 7.4%	485.14 + 6.8%	480.96 + 5.8%	523.89 + 15.3%	539.82 + 18.8%	508.99 + 12.0%	547.16 - 2.4%	495.83 - 11.6%
Total error rate, %	n/a	7.54	7.46	n/a	7.45 - 1.2%	7.38 - 2.1%	8.54 + 13.3%	8.22 + 9.0%	7.09 - 6.0%	7.07 - 6.2%	10.50 + 40.8%	9.40 + 26.0%

Mean values per condition, relative change in % as compared to baseline.
Colour code explanation: Blue – findings of study on ambient temperature [42].
Yellow – findings of study on ambient noise [44]. Gray – findings of this study.

4.6 Comparison between Situational Impairments

In this section, we compare stress-, cold- and noise-induced situational impairments. This comparison allows us to increase our understanding on the impact of different situational impairments, thus contributing towards this growing research agenda.

We present the mean values for the following variables in Table 1: time taken to tap a circle, size of the offset, time taken to memorise an icon, time taken to find an icon, character entry rate, and total error rate in typing. The last two variables are not available for the cold-induced situational impairments, as the authors did not quantify performance during the text entry task under cold ambience [42]. Furthermore, we calculate the magnitude of the impact of each situational impairment, when compared to their respective baseline (as a percentage). Given these calculations and the fact that the experimental tasks were identical between the three studies, we are able to directly compare magnitudes of the effects of each factor causing situational impairments (stress, cold ambience [42], ambient noise [44]).

From the table, we observe that when it comes to hitting buttons and icons on the screen (target acquisition) stress has a more detrimental effect than other situational impairments, even than cold. In fact, our results show that during post-stress recovery, participants are less accurate at hitting targets than when they are exposed to cold ambience. Further, stress affected participants differently when compared to noise: character entry rate dropped by −11.6% and total error rate increased by +26.0%.

Interestingly, however, in Table 1 we see although stress is detrimental to target acquisition, its effect is not as acute as the one of music with fast tempo (+9.1%), and meaningful speech (+8.9%). Nevertheless, we can conclude that the effect of stress is the greatest on memorising time (−12.3%) compared to cold or ambient noise.

5 DISCUSSION

Our findings suggest that even though we do not find a significant effect of stress on throughput in the target acquisition task, it does lead participants to favour speed to the detriment of accuracy. We also show that under stress our participants are quicker to memorise an icon during the visual search task. However, our results do not reveal a significant effect of stress on the text entry task. Below we discuss our findings with regard to existing work. We then discuss the benefits and potential future contributions of this research to the HCI community.

5.1 Effects of Stress on Interaction

Our results show that the target acquisition time and memorising time are significantly shorter when participants tap circles and complete visual search tasks after the post-stress recovery period. Our findings are in line with prior literature, which shows that people tend to rush and require significantly less time to complete tasks when stressed [33]. Moreover, our participants confirm this behaviour during the interview sessions. They mention that stress caused them anxiety and discomfort, and, hence they rushed through the tasks. Furthermore, the participants report that stress affected their concentration and focus. As a result, they did not pay attention to the icon shown during the visual search task. Instead, they proceeded to the next screen for the sake of completing the task.

Additionally, our results show that stress causes our participants to be less accurate when performing target acquisition tasks. This result also reflects prior literature, which shows that people tend to have higher error rates in completing tasks when stressed [33]. Interestingly, this is also the case in the post-stress recovery measurements. During our interviews the participants claimed that they spent this post-stress recovery period self-reflecting on the tasks, which kept them stressed throughout the recovery period. Consequently, their performance during mobile interaction was negatively affected. Our findings are in line with literature [20], as the authors of the TSST report a high cortisol level in participants during the post-stress recovery period.

Nevertheless, our findings do not show a statistically significant effect of stress on effective throughput in the target acquisition task. This result is in line with prior findings by MacKenzie and Isokoski, where they show that throughput remains constant when target acquisition time and accuracy drop during tapping tasks [28]. This can be explained by the fact that throughput accounts for both speed and accuracy and as these two variables change in opposite directions, throughput does not significantly change [28]. However, we note that while throughput remained relatively constant in this scenario, this is likely not to be the case when a stressed user interacts with a real-world application that has a cost associated with errors.

Furthermore, our results show that text difficulty had a larger effect on performance during the text entry task than participant stress levels. Regarding the text entry task several participants ($N = 9$) report that they made comparatively more errors after they experienced stress. While our quantitative results show a tendency towards this being the case, this effect was not statistically significant.

5.2 Contrasting Situational Impairments

Previous work has highlighted the importance of accumulating knowledge within different areas of HCI for the formation of paramount research themes [24, 25]. Here, we contribute towards this notion by contrasting the magnitudes of the effects of different situational impairments on mobile interaction.

Previous work, utilising the same tasks reported in this study, has shown that text entry rate is significantly affected by ambient noise, particularly when considering meaningful speech (speech in a language the participant understands) [44]. However, in our study, participants' performance during text entry (in terms of character entry rate) was not significantly affected by stress, suggesting that stress has a smaller effect on participants' ability to perform text entry compared to meaningful speech. This is not surprising given the nature of the text entry task. Meaningful speech is particularly disruptive when a person is thinking about what they should say or write [30].

Furthermore, in Table 1 we can see that the effect of cold ambience on the target access time was opposite to the one of stress. To be precise, target acquisition time was longer in cold environment [42]; however, it was shorter during the post-stress recovery period (as compared to the relative baselines). This can be explained by the nature of the environment, as cold ambience decreases manual dexterity [60], and hence, increases the completion time for the tasks involving fine-motor manipulations [66]. Whereas, stress is known to increase anxiety [23], thus leading people to rush to complete the tasks [33]. This effect was also highlighted in our qualitative data; and is applicable not only for tasks requiring fine-motor skills, but also for visual search tasks. For example, our participants spent less time on memorising and searching for icons, as compared to the participants from the study presented in [42], where they took longer time both to memorise and find icons. Interestingly, cold-, noise-, and stress-induced situational impairments have a roughly comparable adverse effect on the tapping accuracy. This can be explained by the nature of the task, as both external and internal factors affect accuracy in only one direction – negative. The only difference is the magnitude of the effect, shown in detail in Table 1.

5.3 Implications for Research and Design

Previous research has emphasised the importance of understanding the effects of situational impairments on mobile interaction, as it further enables the construction of sensing mechanisms to detect situational impairments and, thus, adapt the interface accordingly [43]. Our study shows that stress can impair mobile interaction, and, hence, this information can be used to adapt the interface to accommodate such impairments. For instance, to mitigate the effects of stress-induced situational impairments on target acquisition tasks, it is possible to increase target sizes or use techniques proposed in the literature to improve input accuracy, such as GraspZoom [34] and Fat Thumb [6]. GraspZoom allows zooming on a particular part of the screen with a long press using only the thumb [34]. Fat Thumb includes only two interaction gesture modes: panning and zooming, with gesture being defined by the contact size of the thumb [6]. We acknowledge that the effect size of stress on interaction performance might not seem to be strong enough to impair the user experience in real world scenario. However, we expect that when completing more complex tasks on a smartphone, the effect size would be more pronounced.

However, it is necessary to first detect stress before adaptation actually takes place. Wearable sensors have successfully been leveraged for this purpose by measuring physiological measurements such as skin conductivity [50] and heart rate variability [56]. In our study we use HRV measured through a wearable device alongside self-reports, to confirm that participants are indeed being affected by the TSST protocol. Beyond sensor data and self-reports, previous work has shown that daily stress can also be inferred from smartphone usage, personality traits, and weather data [5]. Moreover, the Intel Mobile Heart Health [36] prototype uses data from sources such as mobile phone-based ecological momentary assessment and a small electrocardiograph sensor with an accelerometer to detect changes in heart rate variability, activity, and mood. If individualised threshold values are reached, the mobile phone delivers cognitive behavioural and mindfulness techniques designed to reduce stress [36]. Within the literature on situational impairments, there are also several examples of sensor information being used to detect certain contextual factors. For example, Goel *et al.* [11] used a smartphone's accelerometer to detect if the user is walking. Similarly, Sarsenbayeva *et al.* suggested using the smartphone's battery temperature to detect cold-induced situational impairments [45].

Ultimately, this detection should ideally be performed unobtrusively and without creating additional stress [14]. Unobtrusive and continuous stress detection would benefit mobile device users. For example, an individual being aware of their exposure to stress, could change their behaviour to eliminate unnecessary stressors [14]. A smartphone's operating system that understands the user's application usage behaviour [17, 58], and having detected the user being stressed, could prevent unnecessary notifications or updates being presented [14], and adapt the interface to minimise errors.

5.4 Limitations

We acknowledge a number of limitations in our study. First, the study settings were strictly controlled. It is possible that in a more naturalistic environment, participants can experience a stronger level of stress. However, it was necessary to follow an established protocol to strictly control stress induction and avoid causing harm to our participants. The types of smartphone tasks presented in this study were limited to target acquisition, visual search, and text entry, whereas, in a naturalistic environment, users may perform more complex tasks, requiring more cognitive demand [2]. Nevertheless, in this study we reported a statistically significant effect of stress on basic smartphone tasks (*e.g.,* target acquisition and visual search), which suggests that this effect would be more pronounced when completing more complex tasks during mobile interaction. Furthermore, we did not find any statistically significant effect of stress on text entry tasks. However, we acknowledge that stress might have an impact on text entry performance with more complex sentences. Future research is needed to investigate this assumption. Finally, we restricted our participants to only one interaction mode with the smartphone – using the index finger. We argue that controlling the interaction mode was necessary to draw a fair comparison between the effects of stress, ambient noise [44], and cold ambience [42].

6 CONCLUSION

In this work, we investigate the effects of stress on performance on three common mobile interaction tasks: target acquisition, visual search, and text entry. We use the Trier Social Stress Test to induce stress on participants. Our findings show that the target acquisition time and the time to memorise an icon become significantly shorter during stress and post-stress recovery periods. We also show that stress deteriorates participants' accuracy during target acquisition tasks. These findings can be used to inform how interfaces should adapt to accommodate such impairments.

We then compare the effects of cold-, noise-, and stress-induced situational impairments on performance during mobile interaction. Our results show that the effect was more pronounced on target acquisition tasks in terms of task completion time and accuracy. Our findings on the effects of stress on mobile interaction extend our understanding of situational impairments. This knowledge is paramount to inform the development of adaptive interfaces that accommodate such impairments.

ACKNOWLEDGMENTS

This work is partially funded by a Samsung Global Research Outreach grant and JST ERATO Grant Number JPMJER1501, Japan. Eduardo Velloso is the recipient of an Australian Research Council Discovery Early Career Award (Project Number: DE180100315) funded by the Australian Government.

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Received November 2018; revised January 2019; accepted January 2019

Chapter 6

Quantifying the Effects of Dim Ambient Light on Mobile Interaction

This chapter presents our work on quantifying the effects of dim ambient light on mobile interaction. Prior research has previously established the negative effects of bright sunlight on mobile interaction, as with an increased ambient illuminance, smartphone screens become more challenging to use [77] due to different factors (*e.g.*, reduced screen contrast [220] or screen glare [139]). However, the effect of dim ambient light on mobile interaction has not been thoroughly investigated. The existing knowledge on this area is limited to the study conducted by Lee *et al.* [130], where they establish a negative effect of low ambient illuminance on visual search. In this work we investigate the effect of ambient light on three smartphone tasks (target acquisition, visual search, and text entry) under three ambient light conditions:

- Baseline condition set to 330 lux, which is a standard illuminance level in the office environment [190];
- Surrounding dim illuminance set to 20 lux;
- Dim illuminance caused by participants wearing sunglasses under the baseline condition. The sunglasses were of category 2 non-polarised lenses, commonly used among general population.

The study was conducted in laboratory settings and we strictly controlled for the illuminance level to exclude the presence of natural sunlight or other potential confounding factors (*e.g.*, screen glare). These conditions were selected as they are commonly present during mobile interaction (*e.g.*, in the office room with no windows or in a dark room).

The findings of our study show that dim ambient light negatively affects the target acquisition task. In particular, participants were significantly slower and less accurate when accessing targets under both surrounding and local dim light conditions as compared to the baseline condition. Our results also show that the participants took longer time to memorise icons in visual search task when wearing sunglasses.

This work contributes towards understanding of dim light-induced SIIDs and their effect on smartphone interaction. Technicalities of our approach are detailed in the attached publication in Section 6.1.

6.1 Publication

Sarsenbayeva, Z., van Berkel, N., Jiang, W., Hettiachchi, D., Kostakos, V., and Goncalves, J. (2019, September). Effect of Ambient Light on Mobile Interaction. In *IFIP Conference on Human-Computer Interaction*(pp. 465-475). Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-29387-1_26

Ethics ID: 1852612.1, The University of Melbourne Human Ethics Advisory Group.

Effect of Ambient Light on Mobile Interaction

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Abstract. In this work we investigate the effect of ambient light on performance during mobile interaction. We evaluate three conditions of ambient light – normal light, dimmed light, normal light while wearing sunglasses. Our results show that wearing sunglasses and dimmed light negatively affect reaction time, while dimmed light negatively affects accuracy performance in target acquisition tasks. We also show that wearing sunglasses increases memorising time in visual search tasks. Our study contributes to the growing body of research on the effects of different situational impairments on mobile interaction.

Keywords: Mobile interaction·Situational visual impairments·Ambient light.

1 Introduction

Smartphones have become an integral part of human daily life, and a focus of research conducted in our community [8,9]. People find themselves using their smartphones under various challenging contexts [23]. Factors such as cold ambience [2,18], encumbrance [10], walking [1], and ambient noise [16] have all been shown to hinder smartphone interaction [15] and cause situational impairments [19, 24]. While the effects of a number of situational impairments on mobile interaction have been studied and are established within the HCI research community, many situational impairments remain underexplored. In their overview of situational impairments, Sarsenbayeva *et al.* [15] identify a research gap concerning the effects of ambient light on mobile interaction, despite the fact that it is common to use one's smartphone in varying light conditions (*e.g.,* watching a movie with the lights off or interacting with the device while wearing sunglasses).

Therefore, in this paper we investigate the effect of ambient light conditions on mobile interaction. We quantify mobile interaction performance in terms of three everyday smartphone activities – target acquisition, visual search, and text entry – under three distinct ambient lighting conditions: 1) normal light condition (operationalised as recommended indoor light levels for easy to normal office work [12]), 2) dimmed light condition, and 3) normal light condition while wearing sunglasses. We limit our investigation to the effect of reduced illuminance conditions. We do not study the effect of bright light on smartphone interaction for a number of reasons. First, the existing literature has already established the adverse effect of bright light on performance in visual tasks on mobile device screens [7]. Second, we want to exclude the effect of confounding parameters, such as glare, that is caused by bright light and leads to a decrease in visual task performance on mobile phone screens [7].

Our study shows that dimmed light, as well as wearing sunglasses, negatively affects mobile interaction performance in terms of target acquisition time. We also show that tapping accuracy decreases under the dimmed light condition, while wearing sunglasses increases target memorising time. Our work contributes to the growing body of research in the HCI community on situational impairments.

2 Related Work

2.1 Situational Visual Impairments during Mobile Interaction

Tigwell *et al.* [22] identified ambient light as one of the leading causes of visual situational impairments. Ambient light has been shown to affect people's perception as well as the clarity of a smartphone's display. For example, Gong *et al.* [3] show that as ambient light intensity increases, mobile device screens become more challenging to use. This might be because increasing ambient brightness while decreasing monitor brightness reduces colour differentiation abilities, as found by Reinecke *et al.* [13]. Furthermore, it has been shown that for illuminance levels higher than 1000 lx, participants' visual task performance declines at a faster rate compared to illuminance levels lower than 1000 lx, due to screen glare [7]. Dimmed ambient light has also been shown to visually impair users; however, only limited research has investigated its effect. For example, Lee *et al.* [6] investigated the effect of ambient illuminance on performance while reading e-papers. They found that search speed and illuminance level were directly proportional: with low search speed being associated with low levels of illuminance. Liu *et al.* [7] studied the effect of ambient light on handheld display image quality. The authors found that in darker environments, participants performed better in visual tasks as compared to bright environments. These findings are in line with findings from Kim *et al.* [5] which demonstrate that perceived image quality on screens decreases in bright environments. However, both of the aforementioned studies featured a limited number of participants (3 participants in [7], 10 participants in [5]). Furthermore, both of the studies focused on the perception of image quality on mobile device screens.

3 Method

In this study, we investigate the effect of an environmental factor – ambient light – on mobile interaction. In particular, we focus on mobile interaction under dimmed light conditions. We quantify interaction performance across three typical smartphone tasks: target acquisition, visual search, and text entry. We used the tasks developed and presented in a study by Sarsenbayeva *et al.* [16] in order to directly compare the effect of ambient light-induced situational impairments to the established effects of cold- [2, 18], noise- [16], and stress-induced [14] situational impairments.

3.1 Smartphone Tasks

In this study, we used a Samsung Galaxy S7 smartphone running Android 7.0 with 1080×1920px screen size (similar to the one used in the studies by Sarsenbayeva *et al.* [16, 18]). To minimise sequence effects, participants completed the three tasks in a counterbalanced order. Furthermore, we minimised any potential learning effects by asking our participants to undergo extensive training in all three tasks prior to the start of the actual experiment. The participants completed the tasks in a standing position, interacting with the phone with the index finger of their dominant hand while holding the phone in their non-dominant hand.

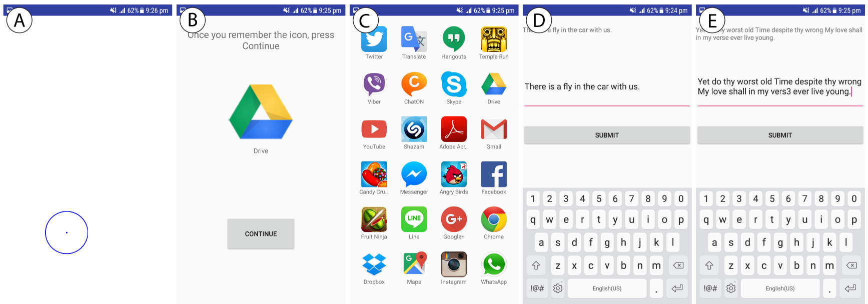


Fig. 1: Interface of the application with Target Acquisition Task (A), Visual Search Task (B-C), and Text Entry Task with user's input for easy and difficult texts (D-E).

Target Acquisition In this task, participants tap circular targets (Radius = 135px) with an indicated centre (Figure 1-A). The targets appear on a random position on the screen, one circle at a time. We asked our participants to tap the centre of the circles as precisely and quickly as possible. We measure participants' performance in terms of their reaction speed (time required to tap targets) and accuracy (offset size).

Visual Search In this task, participants are asked to find a target icon among 24 other icons, arranged according to a 4×6 grid [4]. The participants are first shown the icon, and given as much time as required to memorise it (Figure 1-B). Then, participants must find this icon in the subsequent screen (Figure 1-C). Target icons are selected randomly from the pool, and the icons are placed at random positions on the screen to minimise any potential learning effects. We quantify participants' performance in terms of cognition (time to memorise an icon), reaction (time to find an icon), and accuracy (error rate).

Text Entry In this task, participants are instructed to type a snippet of text shown in a text box. The texts are of two difficulties: 1) easy – consisting of only one sentence with commonly used words (Figure 1-D), and 2) difficult – consisting of several sentences with outdated words (Figure 1-E). For each round, participants are presented a randomly selected easy sentence (10 in total) and a randomly selected difficult sentence (10 in total). We measure how quick (character entry rate) and accurate (error rate) participants were in entering the text.

3.2 Participants

We recruited 28 participants through our university's mailing lists. Participants are between 18 and 33 ($M=23, SD=3.70$) years old. In total, we recruited 19 female and 9 male participants. Our participants have a diverse range of educational background (*e.g.,* Accounting, Actuarial Sciences, Biomedicine, Business, Chemistry, Food Science, Urban Planning). All participants have normal or corrected-to-normal vision (contact lenses) and are right-handed. All of our participants were used to wearing sunglasses.

3.3 Procedure

Our experiment contains three conditions: 1) normal light condition (recommended indoor light levels for easy to normal office work [12]), 2) dimmed light condition, and 3) normal light condition while wearing sunglasses. We followed the guidelines for illuminance standards in a working environment, and hence set the room's illuminance to 335 lx for the normal light condition [12]. In the dimmed light condition, the illuminance of the room was set to 20 lx, a light level which we consider a dark environment to perform most activities. Finally, for the third condition, participants were required to wear non-polarised sunglasses with category 2 lenses under the same illuminance as the normal light condition. Our choice of sunglasses is justified by its popularity of use among the general population, as a category 2 lens provides a medium level of sun glare reduction and UV protection with a visible light transmission of 18∼45% [21]. We ensured that the brightness level of the smartphone was kept constant at a medium level throughout the entire experiment, and disabled brightness auto-adjustment to ensure consistency in the study setup. Furthermore, we counterbalanced the presentation order of the conditions across the participants. At the end of the experiment we conducted semi-structured interviews with each participant to understand their perceived performance during the completion of the tasks. The Human Ethics committee of our university approved this experiment.

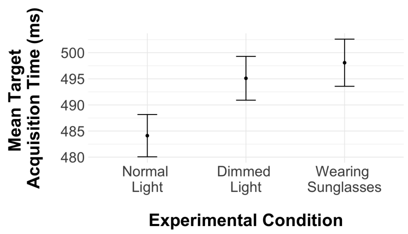
4 Results

To investigate the effect of ambient light on performance during smartphone interaction, we conducted a one-way repeated measures ANOVA on the aforementioned performance-measurement variables. We describe the results of our findings per each smartphone task. We removed extreme outliers from our data (3 individual data points in total from the whole dataset).

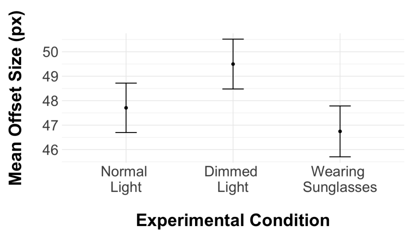
4.1 Target Acquisition

First, we investigated the effect of ambient light on target acquisition time (milliseconds). The result of a one-way repeated measures ANOVA revealed a statistically significant effect of ambient light on target acquisition time ($F(2{,}7607)=8.20, p<0.01$). Post-hoc comparison using the Tukey HSD test (with Bonferroni corrections) showed that there is a significant difference ($p=0.02$) between target acquisition time under the dimmed light condition ($M=495, SD=110$) and the normal light condition ($M=485, SD=103$). Moreover, our results show that the participants took a significantly longer time tapping a target ($p<0.01$) while wearing sunglasses ($M=498, SD=115$) when compared to the normal light condition. However, there was no significant difference between the dimmed light condition and wearing sunglasses ($p>0.05$). Mean values for target acquisition time are presented in Figure 2 (a).

We then examined the effect of ambient light on touch accuracy. A one-way repeated measures ANOVA showed a statistically significant effect of ambient light on the participants' offset size ($F(2{,}7607)=7.32, p<0.01$). Post-hoc comparison using the Tukey HSD test (with Bonferroni corrections) indicated that the offset size was significantly larger under the dimmed light condition ($M=49.50, SD=26.70, p=0.02$) as compared to the normal light condition ($M=47.70, SD=25.80$). We also found a statistically significant difference in offset size between the dimmed light and sunglasses conditions ($M = 46.7, SD = 26.40$, $p < 0.01$). However, there was no significant difference between the offset size under normal light and sunglasses conditions. Mean values for offset size are presented in Figure 2 (b).



(a)



(b)

Fig. 2: Mean Target Acquisition Time and Offset Size (95% CI)

We also studied the effect of ambient light on effective throughput, calculated as proposed by Soukoreff & MacKenzie [20]. A one-way repeated measures ANOVA did not reveal a significant effect of ambient light on the effective throughput during target acquisition tasks.

4.2 Visual Search

We examined the effect of ambient light on the time taken to memorise (milliseconds) and subsequently find an icon (milliseconds). The result of a one-way repeated measures ANOVA revealed a statistically significant effect of ambient light on the time taken to memorise an icon ($F(2{,}2045) = 4.42, p = 0.01$). Post-hoc comparisons using the Tukey HSD test (with Bonferroni corrections) indicated that participants took significantly longer time to memorise icons in the sunglasses condition ($M = 744, SD = 271, p = 0.01$) than the dimmed light condition ($M = 703, SD = 206$). The mean values to memorise an icon are presented in Figure 3. However, we did not find a statistically significant difference between the normal light condition and the dimmed light condition ($p > 0.05$) for the time taken to memorise an icon. We found similar results when comparing the wearing sunglasses condition to the normal light condition ($p > 0.05$).

4.3 Text Entry

In the text entry task we measured participants' performance in terms of time per character entry in milliseconds and total error rate [20]. We calculated character entry rate as time taken to input a character, while the total error rate was calculated as the ratio between the number of total errors and total entered characters. A one-way repeated measures ANOVA did not reveal a statistically significant effect of ambient light on either character entry rate or error rate ($p > 0.05$). We built two gerenalised linear mixed-effect models to describe the effect of ambient light on character entry rate and error rate. None of the predictors had a significant effect on text entry rate.

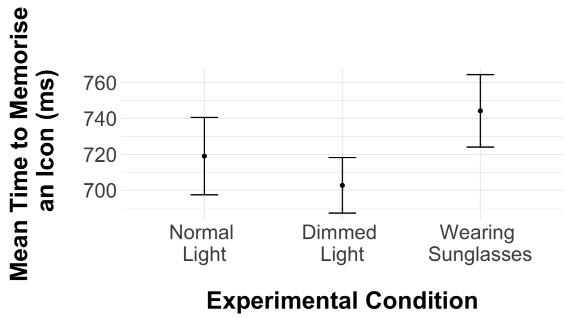


Fig. 3: Mean Time to Memorise an Icon (95% CI)

4.4 Qualitative Results

During the interview, our participants commented on their subjective perception of performance during the smartphone tasks. A number of participants (8 out of 28) mentioned that wearing sunglasses and dimmed light conditions affected their target acquisition time: *"A little longer when I'm wearing the sunglasses."* (P02), *"I was quicker when there was more light." (P12)*, *"Longer time was required under dimmed light" (P06)*. These findings are in line with our quantitative findings which show a negative effect of dimmed light and wearing sunglasses on target acquisition time.

Regarding the self-perceived accuracy during the target acquisition task, half of our participants (14 out of 28) indicated that they were more accurate under the normal light condition as compared to the dimmed light condition. *"In the dimmed light it was harder to accurately tap the center of circles"* (P04). These findings correspond to our quantitative data that shows that under the dimmed light participants were less accurate. Surprisingly, two of our participants claimed they were more accurate under the dimmed light condition, as the contrast of the screen was brighter and they could see the circle clearer: *"In the dim light I felt I was more accurate because the circles were more visible"* (P19).

When we asked the participants about their perceived performance on the time taken to memorising the icon during the visual search task, a large majority of our participants (17 out of 24) stated that the light did not affect their performance. However, these perceptive statements contradict our quantitative results, showing that participants took a significantly longer time when wearing sunglasses as compared to the dimmed light condition. Interestingly enough, one of our participants mentioned that it took them less time to memorise icons under the dimmed light condition: *"When performing in dimmed light it takes less time to memorise icons" (P15).*

Nevertheless, participants reported a negative effect of ambient light on their perceived performance in time taken to find an icon, even though our quantitative analysis does not support this observation. In total, 10 participants mentioned that they believe it took them a longer time to find an icon under the dimmed light: *"It affects me so much. I took a bit longer to find the icons in a dim light condition"* (P18); *"When the light is on, I can find the icon easier compared to when the light is dimmed"* (P13).

Regarding the text entry task, most of the participants (N=19) claimed that the light did not have any effect on their performance. A total of 4 participants believed that they were slower to type under the dimmed light condition and when wearing sunglasses. *"It took me more time to type text under dim light"* (P20). Furthermore, 4 participants claimed to make more errors when the lights were dimmed. *"It was more difficult for me to type the text accurately with dim lighting. I was more confident in typing under normal lighting"* (P12). Nonetheless, our quantitative results did not show any significant support for these statements.

5 Discussion

5.1 Impact of Ambient Light on Mobile Interaction

Our findings show that participants took a significantly longer time to tap a target while wearing sunglasses and under the dimmed light as compared to normal light condition. However, only a minority of our participants (8 out of 28) reported the negative impact of ambient light on target acquisition time. This is an indication that dimmed light caused situational visual impairments in our participant without them noticing it. Previous work has shown that various environmental and internal factors have a different effect on target acquisition time. For example, previous research has shown that participants took a significantly longer time to tap circles under cold ambience due to stiff muscles [17, 18]. However, under music (fast and slow tempo) and urban noise (indoor and outdoor) conditions [16], and when exposed to stress [14], target acquisition time was significantly shorter due to the rhythm of the music, and the anxiety caused by urban noise and stress.

Furthermore, participants were significantly less accurate in target acquisition tasks under the dimmed light condition. This was confirmed in our qualitative data as the participants mentioned that they felt the negative effect of dimmed light on their interaction. In particular, our participants acknowledged that their perceived accuracy when tapping circles in dimmed environment is worse, compared to normal ambient illumination. This may be due to the fact that as the illuminance decreases, retinal dopaminergic activation from photoreceptors drops, and, hence causes a situational visual impairment [11]. In addition, our analysis did not reveal a significant effect of wearing sunglasses on participants' tap accuracy as compared to normal light condition. This might be due to the fact that we used commonly available non-polarised sunglasses that are unlikely to cause strong visual impairments.

However, we observed a negative effect of wearing sunglasses on memorising time in visual search tasks. Moreover, we anticipate that the effect of wearing sunglasses under bright sun light might be exacerbated as the effect of glare contributes to the magnitude of the visual situational impairment. Although ambient light did not have a negative impact on our participants' visual search time, the majority of our participants claimed that it took longer time to find an icon when the light was dimmed. However, this may be the case given the simple nature of the task, as prior research has shown that low illuminance levels are associated with slower search speed [6].

Finally, our analysis did not reveal a negative effect of dimmed light or wearing sunglasses on performance during text entry tasks. This may be due to the fact that we used a limited number of text entry tasks that are not sufficient to observe the effect of ambient light on text entry performance. However, previous work has shown a significant effect on participants exposed to meaningful speech on a similar typing task (i.e. listening to someone speak in a language they understand while typing on their smartphone) [16]. This confirms that different situational factors have a different effect on typical smartphone tasks.

5.2 Accommodating Ambient Light-Induced Situational Impairments

In summary, we demonstrate the negative impact of dimmed ambient light on fundamental smartphone interaction tasks. We argue that accounting for situational visual impairments in mobile interaction is important, as the effect might accumulate as task complexity rises. Moreover, Tigwell *et al.* [22] argue that the value of reducing the effects of situational visual impairments grows as the importance of the task increases. Previous work has proposed different methods to accommodate for situational visual impairments during mobile interaction. For example, in the study by Tigwell *et al.* [23] participants suggested increasing the contrast of the screen to reduce the effect of situational visual impairments. Moreover, Reinecke *et al.* [13] suggest increasing button sizes and adjusting the background colour to reduce the adverse effect of situational visual impairments on mobile interaction. As smartphones already come equipped with an ambient light sensor, these methods can be applied once a detrimental ambient light condition is detected and the user is performing a particular task (*e.g.,* , target acquisition task under the dimmed light). Given that different people have differences in their perception of contrast colours, the ambient light sensor together with adaptive techniques (*e.g.,* screen contrast, background colour) could be used to build personalised interfaces to improve the smartphone interaction experience, beyond simply adjusting the screen brightness as is the case with current devices.

5.3 Limitations

We acknowledge several limitations in this study. First, the study settings were strictly controlled. In particular, we examined only two levels of ambient illumination – normal and the dimmed light, and do not investigate the effect of bright ambient light (outdoor illuminance) on smartphone interaction performance. The reason for this exclusion is to eliminate the effect of additional external factors, such as glare and ambient noise, on smartphone interaction performance. Finally, our experiment is limited to three types of smartphone tasks. We argue that these tasks are representative of the vast majority of activities that typical users undertake while using their smartphone.

6 Conclusion

In this study, we investigate the effect of three ambient light conditions on smartphone interaction performance in target acquisition, visual search, and text entry tasks. We found that dimmed ambient light significantly impairs target acquisition. Participants took a significantly longer time to hit targets while wearing sunglasses or are under dimmed light, as compared to the normal light condition. Furthermore, participants were less accurate when tapping targets under the dimmed light condition. We also show that participants took longer to memorise icons while wearing sunglasses when completing visual search tasks. Our findings enhance the understanding of situational visual impairments impact on mobile interaction and contribute to the growing body of research in the HCI community on situational impairments.

7 Acknowledgements

This work is partially funded by a Samsung GRO grant, and the ARC Discovery Project DP190102627. We also thank Silan Li for her help during data collection.

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Chapter 7

Contrasting the Effects of Different SIIDs on Mobile Interaction

This chapter provides comparison of the effects of the SIIDs: ambient noise, stress, and dim ambient light on mobile interaction presented in Chapters 4, 5, and 6 respectively. Furthermore, this chapter highlights the importance of contrasting the effects of these SIIDs on mobile interaction.

Table 7.1 presents mean values for the variables that are used to quantify the effects of the SIIDs on mobile interaction performance: time taken to tap targets and the size of the touch offset in the target acquisition task, time taken to memorise and time taken to find a target icon in the visual search task, and, finally, time per character entry and total error rate in the text entry task. Furthermore, the table presents the magnitude of the impact of each of the SIIDs in percentage when compared to their respective baselines. This direct comparison of magnitudes is possible due to the fact that the protocol followed in the studies presented in Chapters 4, 5, and 6 was identical. Moreover, each baseline condition presented in Table 7.1 was controlled by excluding additional confounding factors that could possibly lead to decrease in performance during mobile interaction. In particular, we ensured that the baseline conditions for each of the studies presented in Chapters 4, 5, and 6 were silent, warm, stress-free, and illuminated with normal ambient light.

It is important to note that Table 7.1 was partially presented in the publication presented in Chapter 5; however, it did not include the data for the effects of dim ambient light. Hence, Table 7.1 in this chapter presents complete data on the effects of SIIDs investigated within the scope of this thesis. However, this chapter will mostly focus on and discuss the effects of SIIDs that were statistically significant on mobile interaction performance as was established in the studies presented in Chapters 4, 5, and 6.

7.1 Target Acquisition Task

From Table 7.1 we can observe that particular SIIDs have a more pronounced effect on mobile interaction performance during the target acquisition task. For example, when exposed to the cold environment and dim light, participants took longer time to tap on the targets as compared to the respective baselines, *e.g.,* warm environment and normal light. The effect of cold ambience can be explained by the fact that cold temperature decreases the dexterity of extremities, fingers in this case; hence, increases task completion time [24, 106]. According to Table 7.1, dim ambient light also slowed down the target access time in the target acquisition task. This effect can be explained by the reduced colour differentiation abilities due to dim light [220] as well as reduced photoreceptors' dopaminergic activation [189], resulting in prolonged target access time and reduced accuracy. Table 7.1 also demonstrates that under meaningful and meaningless speech conditions, target acquisition time was longer as compared to the baseline condition (silence). However, this effect was not statistically significant.

In contrast to cold ambience and dim light, under music conditions (both fast and slow), the target acquisition time was significantly lower than compared to the respective baseline (*i.e.,* silence). These findings are in line with literature, as it has been previously shown that music tempo influences people's task completion time [44, 162, 166, 167]. In particular, research has shown that under fast tempo music, people tend to complete their tasks, such as eating and drinking, faster [162, 166, 167]. Nevertheless, according to literature, slow tempo music is associated with slower task completion times [44]; however, our study demonstrates that when listening to music with both slow and fast tempo, participants were quicker to access targets as compared to the silent condition. We argue this was due to the fact that in our study we used the same musical composition – Bach's "Brandenburg Concerto No. 2" sampled at a lower rate for slow tempo music condition (60 bpm).

Furthermore, target acquisition time was faster when participants were experiencing and recovering from the induced stress as compared to no stress baseline. These findings were also in line with the existing literature [163], as it has previously been shown that due to stress, people experience anxiety [128] and rush through their tasks [163]. Table 7.1 also shows that the effect of stress was the most profound one on target access time compared to other SIIDs presented in the table. This implies that when designing adaptive interfaces to accommodate the effects of SIIDs on mobile interaction performance, from the ones presented in Table 7.1, stress should be given a higher priority as its' effect on target acquisition task is more severe.

Interestingly, regardless of the SIID type, we can observe in Table 7.1 that when the target acquisition time decreases, the size of the offset grows; hence, the accuracy of the touch drops. This can be explained by the fact that when the participants favour speed of target acquisition task, they neglect the accuracy [150, 249]. In case of cold ambience, while the target acquisition time increases, the accuracy drops due to the loss of dexterity in fingers [24, 106].

7.2 Visual Search Task

The visual search task had two components that were quantified within the scope of this thesis: target icon memorisation and target icon search. The effects of SIIDs on this mobile task was not as diverse as on the target acquisition task. From Table 7.1 it can be observed that SIIDs had a significant effect on target memorisation time, but not the target visual search time.

For example, in the study presented in [231], cold ambience had a significant negative effect on target memorisation time as compared to the warm environment. This might be due to the fact that cold ambience can negatively affect cognitive abilities of people [61]; however, the exposure to cold needs to be prolonged (at least 45 min [61]). This can partially explain why the authors did not observe negative effect of cold ambience on visual search time [231].

Moreover, in the study presented in Chapter 4 and as demonstrated in Table 7.1, we observed that under urban indoor noise, icon memorisation time was significantly lower as compared to the memorisation time in the baseline condition. This might be due to the fact that urban noise was not pleasant for the participants to experience; hence, they tried to "escape" this condition and rushed through the task (as mentioned in the qualitative data). Similarly, in the study presented in Chapter 5, memorisation time was significantly shorter when participants were experiencing and recovering the induced stress. We argue that the reason behind such behaviour is again anxiety [128] that has shown to prompt people to rush through the tasks [163].

Finally, according to Table 7.1, it can be observed that wearing sunglasses had a negative effect on icon memorisation time, but not on icon search time. Similarly, there was no significant effect of ambient noise and stress on visual search time. This might be because the visual search task was not complex enough to observe stronger effects of these SIIDs and further research is needed to fully understand its impact on mobile interaction.

7.3 Text Entry Task

From Table 7.1 it can be observed that the effect of outdoor urban noise had a negative influence on participants' performance during the text entry task as demonstrated in the study presented in Chapter 4. In particular, the participants took significantly longer time per character entry when exposed to urban outdoor noise condition as compared to the silence. This might be because urban outdoor noise is distracting in nature [19], and, hence, added to the cognitive load of the participants who needed to concentrate to complete the text entry task [18]. As a result, participants took longer time to complete the text entry task when being exposed to urban outdoor noise condition.

Furthermore, Chapter 4 demonstrates the negative effect of meaningful speech on participants' performance during the text entry task: time per character entry was significantly longer under the meaningful speech condition as compared to the silent condition. Such behaviour can be explained by the distracting nature of meaningful speech that also increases people's cognitive load [261]. As text entry task also requires concentration and occupies participants' cognitive load, presence of meaningful speech adds to the cognitive load and deteriorates performance during the text entry task. Interestingly, this effect was not observed in the meaningless speech condition on the text entry task possibly due to the fact that it was easier for participants to ignore the meaningless speech, hence decrease its' effect on cognitive load, as they did not understand it. Finally, the effect of both outdoor urban noise and meaningful speech was not observed on the error rate during text entry. This might be due to the limited number of text entry messages that did not let us observe statistical significance of these SIIDs on the text entry task.

Finally, the effects of dim ambient light and the effects of stress on the text entry task were not statistically significant in the studies presented in Chapters 5 and 6 neither in terms of time per character entry nor error rate. This might be due to several reasons. First, the number of text entry messages within the task was limited and, perhaps, was not sufficient enough to observe the effect of these SIIDs (stress and dim ambient light) on text entry performance. Second, the SIIDs were strictly controlled according to the protocol. It is possible that under naturalistic conditions, the effects of both stress and dim ambient light might be stronger than the ones presented in our studies. It is possible that under stronger levels of stress and dim ambient light while completing more complex text entry tasks, the effects of these SIIDs might be more profound and remain to be investigated in future work. Overall, from Table 7.1 we can observe that meaningful speech has a greater detrimental effect on the text entry task performance; hence, meaningful speech should be given higher priority to accommodate mobile interaction during text entry in circumstances with multiple SIIDs being detected.

In addition, the effects of cold ambience on the text entry task is not presented in Table 7.1, as the authors of [231] did not investigate and did not report this data in their study. Hence, it is not applicable to review the effects of cold ambience on text entry performance within the scope of this thesis. Future work could further investigate the effects of different ambient temperatures on text entry performance.

7.4 Implications for Design and Summary

Our findings demonstrate that different SIIDs have different effects on mobile interaction tasks. This knowledge could be considered when designing detection mechanisms or adaptive user interfaces for smartphones and other ubiquitous technology that require mobile interaction in presence of SIIDs. For example, to reduce the effects of cold, stress, and ambient noise on target acquisition task performance, mobile interfaces could increase the size of the targets or actuate input techniques directed to improve accuracy, presented in literature [26,37,116].

Moreover, as smartphones and other ubiquitous devices come equipped with a number of sensors, both contextual, sensor, and input data can be used to detect the presence of SIIDs. For example, built-in microphone of the device could be used to detect noise-induced SIID, while built-in ambient light sensor could be used to detect ambient light-induced SIIDs.

Furthermore, our findings could be used to suggest or avoid using certain input techniques when particular SIIDs are detected. For instance, the interface could avoid using voice assistance in the presence of ambient noise; however, it could be a preferred input technique when cold-induced SIIDs are sensed. In addition, the interface could potentially warn the user about possible frostbite risks if long exposures to cold has been recorded by the device [231]. Similarly, to decrease the effect of meaningful speech on the text entry task, the interface could launch adaptive keyboard to improve user experience and minimise errors [70].

To summarise, these comparisons enhance our understanding of the effects of different SIIDs on mobile interaction, and therefore, accumulate knowledge on SIIDs research and contribute to the research agenda. This knowledge can also assist researchers and designers in developing mechanisms for accommodating SIIDs when a combination of them is present and when particular tasks are being completed.

Table 7.1: Comparison of the Effects of SIIDs against Respective Baseline

	Baseline				Situational Impairments										
Mean (SD)	**Warm**	**Silent**	**No stress**	**Normal Light**	**Cold**	**Music Fast**	**Music Slow**	**Urban Indoor**	**Urban Outdoor**	**Speech Meaningful**	**Speech Meaningless**	**Stress**	**Post-Stress Recovery**	**Dim Light**	**Wearing Sunglasses**
Time to tap a circle, ms	593.00 (137.89)	591.84 (125.07)	538.68 (127.58)	485.00 (103.00)	603.00 * + 1.7%	577.76 * - 2.4%	574.15 * - 3.0%	583.56 * - 1.4%	573.56 * - 3.1%	592.81 + 0.2%	609.38 + 3.0%	534.77 * - 0.7%	520.18 * - 3.4%	495.00 * +2.27%	498.00 * +2.89%
Offset size, px	41.34 (40.89)	39.38 (35.26)	46.47 (25.57)	47.70 (25.80)	42.66 * + 3.1%	42.95 +9.1%	42.11 * + 6.9%	41.06 + 4.3%	40.91 + 3.9%	42.90 + 8.9%	39.47 + 0.3%	49.14 * + 5.7%	50.20 * + 8.0%	49.50 * +3.77%	46.70 -2.09%
Time to memorise an icon, ms	815.00 (150.15)	748.76 (253.89)	800.51 (331.15)	719.00 (290.00)	854.00 * + 4.8%	737.71 - 1.5%	745.15 - 0.5%	712.11 * - 4.9%	743.56 - 0.7%	753.20 + 0.6%	738.90 - 1.3%	714.52 * - 4.6%	702.31 * - 12.3%	703.00 -2.25%	744.00 +3.47%
Time to find an icon, ms	1632.24 (1235.27)	1587.74 (871.95)	1602.45 (1315.82)	1499.00 (827.03)	1942.46 + 19.0%	1564.70 - 1.4%	1753.19 + 10.4%	1543.12 - 2.8%	1633.15 + 2.9%	1637.54 + 3.1%	1520.99 - 4.2%	1496.50 - 6.6%	1506.38 - 6.0%	1477.07 -1.46%	1513.00 +0.93%
Character entry rate, ms/char	n/a	454.39 (219.95)	560.88 (173.96)	532.20 (121.00)	n/a	488.11 + 7.4%	485.14 +6.8%	480.96 + 5.8%	523.89 * + 15.3%	539.82 * + 18.8%	508.99 + 12%	547.16 - 2.4%	495.83 - 11.6%	519.01 -2.48%	527.00 -0.94%
Total error rate, %	n/a	7.54 (7.72)	7.46 (6.63)	5.55 (4.81)	n/a	7.45 - 1.2%	7.38 - 2.1%	8.54 + 13.3%	8.22 + 9.0%	7.09 - 6.0%	7.07 - 6.2%	10.50 + 40.8%	9.40 + 26.0%	4.94 -10.99%	5.06 -8.83%

* *indicates statistically significant effect*

Chapter 8

Sensing Cold-Induced SIIDs

Previous work has already quantified the effects of cold environments on smartphone interaction [76, 231]. Cold has been shown to have a negative effect on fine-motor performance during mobile interaction due to decreased dexterity and stiffness of the muscles [76]. In particular, participants took significantly longer time and were less accurate when completing target acquisition tasks under cold ambience when compared to a warm environment. The study demonstrates the importance of accounting for cold-induced SIIDs that might impair mobile interaction [231].

This chapter presents our work where we propose a sensing mechanism to detect cold-induced situational impairments using an off-the-shelf smartphone (RQ3). Current smartphones are equipped with different sensors that can be used to detect the presence of different situational impairments. For example, the ambient light sensor can be used to detect ambient light-induced SIIDs, while ambient noise-induced situational impairments can be detected with the help of the device's built-in microphone. Internal SIIDs, such as stress, can be detected via wearable devices. For example, physiological data collected from wearable sensors – HRV and EDA [161] – can indicate the presence of stress. Nevertheless, despite the established adverse effect of cold-induced situational impairments [231] on mobile interaction, the researchers did not propose a sensing mechanism to detect them.

This is particularly challenging, as there are several factors (*e.g.,* context, location, interaction duration) that need to be accounted for when designing a sensing mechanism to detect cold-induced SIIDs. For example, a general weather forecast cannot be used for this purpose as while indoor/outdoor detection mechanisms for smartphones exist [7], exposure to cold conditions may vary for a myriad of reasons (*e.g.,* the user is wearing gloves or is located in an somewhat environmentally shielded outdoor location).

Our work suggests using the smartphone's built-in battery temperature sensor to infer changes in users' finger temperature. This approach is fairly reliable as it demonstrates a similar trend in behaviour between the smartphone battery temperature, and users' finger temperature in cold and warm environments:

decreases in the cold ambience, and increases in the warm environment. In particular, we found a high correlation between these two variables ($r = 0.86$). Our findings contribute towards building sensing mechanisms to detect cold-induced SIIDs using an off-the-shelf smartphone. The details of our approach can be found in the attached publication in Section 8.1.

8.1 Publication

Zhanna Sarsenbayeva, Niels van Berkel, Aku Visuri, Sirkka Rissanen, Hannu Rintamaki, Vassilis Kostakos, and Jorge Goncalves. 2017. Sensing Cold-Induced Situational Impairments in Mobile Interaction Using Battery Temperature. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 98 (September 2017), 9 pages. DOI: `https://doi.org/10.1145/3130963`

Ethics for this study was obtained from the University of Oulu (Finland) under local ethics advisory group.

Sensing Cold-Induced Situational Impairments in Mobile Interaction Using Battery Temperature

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Previous work has highlighted the detrimental effect of cold ambience on fine-motor skills during interaction with mobile devices. In this work, we develop a method to infer changes in finger temperature of smartphone users without the need for specialised hardware. Specifically, we demonstrate that smartphone battery temperature is a reliable gauge for determining changes to finger temperature. In addition, we show that the behaviour of smartphone battery temperature in cold settings is consistent across different smartphone models and battery configurations. Our method can be used to determine cold-induced situational impairments, and trigger interface adaptations during mobile interaction.

CCS Concepts: • **Human-centered computing** → Empirical studies in HCI; • **Human-centered computing** → Ubiquitous and mobile computing; • **Human-centered computing** → Smartphones

KEYWORDS

Smartphones, ambient temperature, battery temperature, situational impairments, finger temperature, cold chamber.

ACM Reference format:

Zhanna Sarsenbayeva, Niels van Berkel, Aku Visuri, Sirkka Rissanen, Hannu Rintamaki, Vassilis Kostakos, Jorge Goncalves. 2017. Sensing Cold-Induced Situational Impairments in Mobile Interaction Using Battery Temperature. *PACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 98 (September 2017), 9 pages.
DOI: 10.1145/3130963

This work is partially funded by the Academy of Finland (Grants 276786-AWARE, 286386-CPDSS, 285459-iSCIENCE, 304925-CARE), the European Commission (Grant, 6AIKA-A71143-AKAI), and Marie Skłodowska-Curie Actions (645706-GRAGE).

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2474-9567/2017/September- 98 $15.00

https://doi.org/10.1145/3130963

1 INTRODUCTION

Cold ambience is known to affect fine-motor skills during interaction with mobile devices. This is due to the fine-motor dexterity loss caused by drops in finger temperature [6,13]. However, while previous work has shown that finger temperature is an important consideration when designing mobile phone applications, no reliable way of inferring finger temperature in situ has been proposed without the need for external measurement devices (*e.g.*, skin thermistors).

Future smartphones may come with embedded environmental temperature sensor to gauge ambient temperature, but this is still not the case today. In our work, we make creative use of existing smartphone sensors to gauge finger temperature. Specifically, we investigate if finger temperature can be inferred from the smartphone's battery temperature. The literature contains a growing list of examples where smartphone sensors originally intended for a particular function can actually be appropriate for a wholly different use case. For example, researchers have shown how to transmit data using the magnetometer [9], or determine social context through Bluetooth traces [2].

Here we demonstrate that it is possible to leverage data on smartphone battery temperature to infer fluctuations of a user's finger temperature during interaction. We show a significant correlation between battery and finger temperature, and as such one can be used to infer the other. Our method can infer changes in users' finger temperature using off-the-shelf smartphones without the need for additional sensors or hardware.

2 RELATED WORK

2.1 Environmental Sensing Using Smartphones

Previous work has described the use of smartphone sensors to better understand surrounding weather conditions. For instance, Mass & Madaus [10] discuss the use of smartphone pressure sensors for surface pressure observations. They describe that a fine-grained network of smartphone users would allow for high-resolution weather prediction as pressure readings are "*not influenced by characteristics of the underlying surface, as are temperature and wind*" [10], and therefore readings are not influenced by different contexts (*e.g.*, shade, urbanisation).

Overeem *et al.* [12] also suggest that smartphones can be used as an effective instrument to study environmental and climate changes. Sensor data such as air humidity, air pressure, and air temperature can be used for data assimilation in weather prediction models, water management, and urban planning [12]. More relevant to our work, they report the analysis of a six-month dataset of 2.1 million battery temperature readings from eight major cities collected using the OpenSignal[1] Android application. They found that daily battery temperature was strongly correlated with the observed daily air temperature ($r = 0.82$) [12]. In addition, literature shows a substantial impact of ambient temperature on human's body temperature, particularly for extremities (*e.g.* fingers, toes) [11]. These findings provide us with strong motivation towards investigating the possibility of inferring changes in user finger temperature based on changes in smartphone battery temperature.

2.2 Extending Smartphone's Capabilities

The literature also contains examples on the use of smartphones in combination with specialised devices for environmental sensing. A combination of general smartphone sensors and purpose-made (add-on) sensors allows for the collection of sensor data not feasible with a standalone smartphone. By distributing 8000 small add-ons for regular smartphones among the Dutch population, Snik *et al.* [14] deployed a 'citizen science' experiment to carry out aerosol measurements of high temporal resolution. "*The optical design of iSPEX uses the smartphone camera as the detector, and the iSPEX add-on produces a spectrum of the light that entered the slit [...]*" [14].

[1] http://opensignal.com

In a different project, researchers developed an attachment for smartphones to crowdsource the collection of pollution data [8]. Combining this data with the GPS sensor of the mobile phone allowed for a more detailed understanding of urban air pollution.

Aram *et al.* [1] monitored changes in temperature and humidity using a Bluetooth-based acquisition system. The system consisted of device with a built-in temperature and humidity sensor, and a microcontroller wirelessly transmitting the climatic parameters to a receiver via Bluetooth. The device was left in a climatic chamber to monitor the temperature drop from 25 ºC down to -20 ºC followed by a temperature rise back to 25 ºC, as well as a constant humidity level. The results show that temperature values obtained by the system were consistent with the temperature values inside the climatic chamber, but not for humidity values. They suggest that their approach might be useful to observe climate conditions for small environments, such as laboratories, home rooms, or medical spaces, and to trigger alarms when these conditions change [1].

2.3 Impact of Situational Impairments on Smartphone Use

Previous work suggests that smartphone interfaces should be adapted when used under various situational impairments, such as dynamic state of the phone [5], ambient light and noise [16], movement [4], and cold ambience [6,13]. A number of different solutions have been developed to overcome these situational impairments when interacting with a mobile device. For example, Goel *et al.* [4] suggest adapting the keyboard interface when walking is detected to improve typing experience. This adaptive interface reduced errors and increased typing speed. Moreover, Wobbrock [16] argues that a better understanding of situational impairments can in addition contribute to improved accessibility and adaptive user interfaces. Furthermore, he considers the possibility that solutions designed for people with physical impairments can be applied to those with situational impairments during mobile interaction (*e.g.*, finger arthritis and people with cold fingers [16]).

On the topic of situational impairments caused by cold temperatures, previous work has shown that user performance when completing tapping tasks on a smartphone is affected by finger temperature. As a result of this finding, the researchers suggest adding finger temperature as a parameter in Fitts' Law modelling [6]. Furthermore, Sarsenbayeva *et al.* [13] show that precision and quickness are adversely affected by cold temperatures. While the researchers provide design suggestions for mobile device interface adaptation in cold environments, they do not describe how user exposure to cold ambience can be detected in a naturalistic setting (*i.e.*, without temperature sensors attached to the user's fingers). Hence, we extend previous work by proposing a method to determine changes in finger temperature by considering the smartphones' battery temperature.

3 STUDY

We conducted two experiments to 1) assess the effect of a cold environment on the battery temperature of several smartphone models, and 2) investigate the relationship between smartphone battery temperature and human finger temperature.

3.1 Experiment 1: Device Comparison

We conducted a comparative study of changes in battery temperature over time using multiple handsets. Our objective was to investigate whether different phones and batteries behave similarly in cold settings. We considered four different smartphones that vary in manufacturer, size, battery capacity, and other factors (see Table 1). Given the wide range of characteristics in our selected phones, we argue that they provide a good representation of existing models in the market.

Table 1. Specifications of smartphones used in our study.

	Motorola Moto G3	**Samsung Galaxy S4 Mini**	**Huawei Nexus 6P**	**LG Nexus 5X**
Dimensions (H x D x W)	142.1 x 72.4 x 11.6 mm	124.6 x 61.3 x 8.49 mm	159.3 x 77.8 x 7.3 mm	147.0 x 72.6 x 7.9 mm
Weight	155 g	107 g	178 g	136 g
Screen size	5.0”	4.3”	5.7”	5.2”
Body material	Polycarbonate	Polycarbonate	Metal	Polycarbonate
Battery type	Li-Ion	Li-Ion	Li-Po	Li-Po
Battery capacity	2470 mAh	1900 mAh	3450 mAh	2700 mAh
Removable battery	No	Yes	No	No

The experiment took place in a medical testing facility, in two separate rooms with independent climate controls. As previous work identified the effect of cold ambience on performance during mobile interaction [13], we replicated the protocol to determine if under the same conditions we could use battery temperature to infer finger temperature. Namely, we set the cold room temperature to -10 °C, with wind velocity below 0.1 m/s and 70-75% humidity, while the warm room was set to 20 °C. All four smartphones were rotated between these two spaces to measure fluctuations in battery temperature: 14 minutes in cold temperature, 14 minutes in room temperature, 14 minutes in the cold temperature, and again 14 minutes in room temperature. We developed a custom Android application to record smartphone battery temperature for each device every 30 seconds during the experiment. Due to its power saving features, Android only allows polling of battery related data when an event is registered by the device’s battery. Therefore, we ensured the triggering of an event on smartphones’ battery every 30 seconds by plugging and unplugging the devices into an electrical outlet to collect battery temperature measurements.

3.1.1 Results. Fig. 1 shows the battery temperature fluctuation for each smartphone used in Experiment 1. Vertical lines represent the start of the experiment in each of the rooms. We calculated the Pearson product-moment correlation coefficient between each device to assess the relationship between the measured battery temperatures. A statistically significant positive correlation was observed between the battery temperatures of all four devices (Table 2).

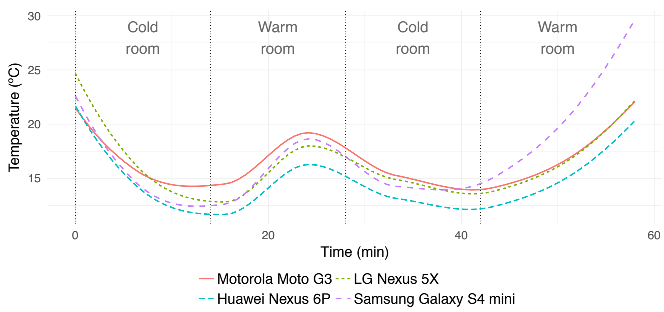

Fig. 1. Smartphone battery temperature change.

Table 2. Pearson correlation coefficients between battery temperatures of the used smartphones.

	Motorola Moto G3	Samsung Galaxy S4 Mini	Huawei Nexus 6P	LG Nexus 5X
Motorola Moto G3	-	0.96	0.98	0.92
Samsung Galaxy S4 Mini	0.96	-	0.99	0.88
Huawei Nexus 6P	0.98	0.99	-	0.91
LG Nexus 5X	0.92	0.88	0.91	-

3.2 Experiment 2: Finger & Battery Temperature

In this experiment, we investigate if smartphone battery temperature and human finger temperature co-vary when exposed to changing ambient temperature. The experimental design was adopted from previous work [13]. We recruited 24 participants for our experiment through social media and mailing lists. We controlled for gender by having an equal distribution of males and females. All participants had lived in cold climates (*e.g.*, Scandinavia) for more than six months and owned a smartphone for at least one year. We also controlled participants' clothing by instructing them to wear a single layer of trousers and top garments on the day of the study and providing them with additional winter attire.

After participants were briefed on the purpose of the study, we asked them to sign a consent form if they agreed to the study's specifications. Participants were then instrumented with thermal sensors attached below the nails of their index finger and thumb on the back of their dominant hand. Thermal data was logged every 1 second using a mobile battery-powered Grant Squirrel meter/logger series 1000 (Fig. 2), allowing us to measure finger temperature, as described in [6,13]. We chose to only instrument these two fingers as they are the ones most likely to be used during one-handed or two-handed interaction with a smartphone. Participants did not wear gloves during the experiment and were asked to not place their hands inside of their pockets. The experiment took place in the same medical facility and rooms as Experiment 1, using the same room temperatures. Participants were asked to wear additional winter attire provided by us when exposed to the cold chamber (Fig. 2). Following the design of Sarsenbayeva *et al.* [13], participants alternated between the two rooms (cold-warm-cold-warm), and we recorded both battery and finger temperature every 30 seconds. During the study, participants were asked to use a provided smartphone to complete target acquisition tasks for 4 minutes in 3 different instances (at 1:00, 6:00 and 11:00, with a 1-minute break in between) for each condition (cold/index, cold/thumb, warm/index, warm/thumb). The hand posture was randomised and counterbalanced. We avoided using colder temperatures in our study (*i.e.,* below -10 °C) to ensure the wellbeing of the participants. The experimental design was approved by the ethics committee of our university.

3.2.1 Results. A Pearson product-moment correlation coefficient was calculated to assess the relationship between participants' finger temperatures (index and thumb) and the phone's battery temperature. A positive correlation was observed for both fingers (index: $r = 0.86$, $p < 0.01$; thumb: $r = 0.85$, $p < 0.01$). Fig. 3 shows the changes in finger temperature and the smartphone's battery temperature throughout the experiment for each participant. Furthermore, our results show that participants' finger temperature *decreased* on average 0.73 °C per minute in the cold room, and *increased* on average 0.79 °C per minute in the warm room.

Fig. 2. Left: Grant Squirrel meter/logger (series 1000) and a participant's hand with thermal sensors attached. Right: Participant in the cold chamber and in the warm room.

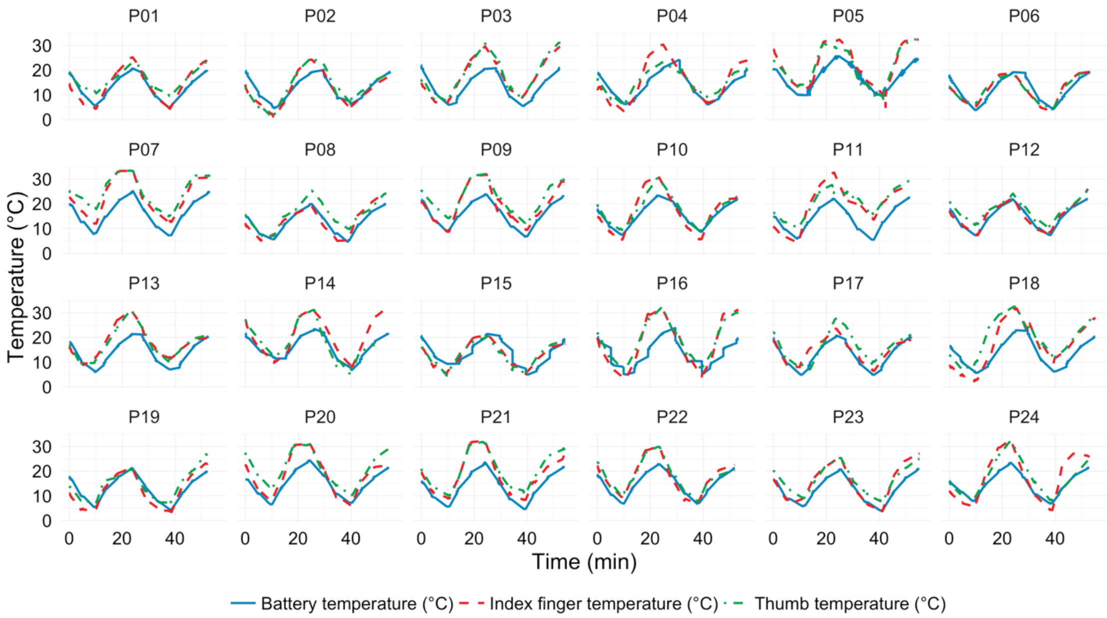

Fig. 3. Participants' finger temperature and smartphone battery temperature.

4 DISCUSSION

4.1 Inferring Cold-Induced Situational Impairments

Previous work has shown that ambient temperature is highly correlated with smartphone battery temperature [1,12], and that ambient temperature has a significant impact on body temperature, particularly the extremities (*e.g.* fingers) [11]. In our work, we investigate the missing link regarding the relationship between finger temperature and smartphone battery temperature (Fig. 4). Our results demonstrate that smartphone battery temperature is highly correlated with users' finger temperature (index: r = 0.86, thumb: r = 0.85) and can therefore be used to infer potential cold-induced situational impairments during mobile interaction for both interaction modes (one-handed and two-handed).

Our work demonstrates that changes in smartphone battery temperature along with other factors (*e.g.*, user input pattern) can be leveraged to signal the need to adapt the smartphone for cold environment. In addition, we show that this can be achieved without adding any additional sensors to the smartphone. Our approach of detecting a situational impairment corresponds to the method used by Goel *et al.* [4], where an accelerometer (a general-purpose sensor on most smartphones) was used to detect and reduce situational impairments induced by walking.

While previous work was able to achieve high accuracy when measuring device surface and screen temperature through additional sensors [3], an approach with add-on sensors aimed at measuring finger temperature is currently not feasible in real world situations. This is a challenge for researchers or interface designers who wish to adapt the interaction and interface when cold-induced situational impairments are detected. Our method shows that off-the-shelf smartphones can be used to detect users' finger temperature, thus providing a practical way to detect and accommodate for cold-induced situational impairments.

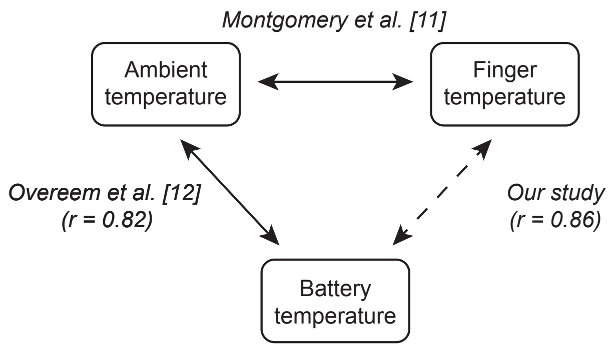

Fig. 4. Smartphone battery temperature relation to ambient temperature and finger temperature.

4.2 Method Applicability

Previous work has argued that cold environments cause significant deterioration of fine-motor performance when interacting with the mobile device [6,13]. To improve fine-motor performance during mobile interaction, it is important for the device to be aware of the changes in a user's finger temperature and adapt its interface accordingly. Here we present an unobtrusive method to detect these cold-induced situational impairments during mobile interaction.

In practice, our method can be used as follows. When a user initiates interaction with the device, the device registers its current battery temperature. Subsequent decreases in battery temperature *while* the user is still interacting with the phone can then be used to infer drops in finger temperature. Once a certain threshold of finger temperature decrease has occurred, the smartphone interface should then adapt accordingly or provide warnings to the user. It is important to note that for our method to work, finger temperature inference can only occur *during* interaction. When not using their phone, users might put their hands in their pockets or warm up their hands through other means.

Finally, previous work has shown that a decrease of just a few degrees Celsius can affect mobile interaction performance [6]. Here, we show that participants' finger temperature dropped on average 0.73 °C per minute under our cold exposure conditions. However, at temperatures lower than -10 °C, the cooling rate of the fingers would be accelerated. This means that decreases in mobile interaction performance would occur in increasingly shorter spans of time.

4.3 Limitations

This study has several limitations. While the choice for a constant room temperature is well motivated (temperature hardly changes during a typical session of smartphone usage [15]), we were limited in the actual temperature level imposed on our participants due to safety concerns. While outdoor temperatures in some parts of the world reach much lower temperatures than -10 °C, we decided not to study more extreme scenarios. In addition, we have not been able to test a wider range of smartphone models due to both time and financial constraints. However, the range of smartphones used in our study (Table 1) does show a considerable level of diversity. This, combined with the high correlation in our results, provides us with sufficient confidence that our results hold true for a much larger selection of smartphone devices.

Further, participants were instructed to not wear gloves or warm their hand by any other means, unlike in naturalistic settings where they could wear touchscreen gloves to interact with their devices or warm their hands inside of their pockets. This was by design as we wanted to: 1) avoid touch inaccuracies during mobile interaction, and 2) observe steady finger temperature drop.

Finally, we did not run compute-intensive applications on the devices during our experiment as we chose to focus on more typical interactions that are more likely to occur in outdoor cold environments.

5 CONCLUSION

In this study, we demonstrate that changes in smartphone battery temperature can be used to infer changes in users' finger temperature. By doing so we also filled an important gap in the literature. While previous work has identified a relationship between ambient temperature and finger temperature, and between ambient temperature and battery temperature, our work is the first to establish a relationship between finger temperature and battery temperature. This is an important finding as it shows that cold-induced situational impairments can be predicted using off-the-shelf smartphones. This information can then be used to adapt mobile interfaces to overcome cold-induced situational impairments or simply to provide warnings to the user on over-exposure to cold environments.

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Received May 2017; revised June 2017; accepted July 2017

Chapter 9

Discussion

This chapter contemplates on the research contributions presented in Chapters 4, 5, 6, and 8 of this thesis in relation to existing literature and answers research questions defined at the beginning of the thesis. We conclude this chapter with the limitations faced by the studies included in this thesis and offer a pathway for future work to be conducted within this research area.

9.1 RQ1. What are the effects of different SIIDs on mobile interaction?

This thesis demonstrates that different SIIDs have different effects on mobile interaction. We also show that the effects of SIIDs varied depending on the smartphone tasks.

9.1.1 Ambient Noise

In Chapter 4 we demonstrate that distinct types of ambient noise affect mobile interaction performance in different ways. For example, music with both fast and slow tempo decreased participants' target access time; hence, accelerated their performance in the target acquisition task. Regardless this improvement in target access time, participants were significantly less accurate when accessing targets as the touch offset size increased under both music conditions when compared to the baseline condition. These findings are in line with literature that has previously shown that although music accelerates task performance speed, this improvement comes at a cost of reduced accuracy [52]. However, the effect of music was limited to the target acquisition task only, and it did not have a statistically significant effect on neither the visual search nor the text entry tasks. In addition, the qualitative data from this study showed that music was in general positively perceived by the participants and added a "fun factor" to the task. Participants felt that under the music condition they were quicker tapping on the targets as they wanted to be *"in line with the music rhythm"* (12 out of 24 participants).

We then show that urban noise had a detrimental effect on mobile interaction performance. Similar to music condition, under both urban indoor and outdoor noise types, participants were quicker to tap targets; however, unlike in the music conditions, this improvement in speed did not affect their accuracy. Furthermore, when exposed to urban indoor noise condition, participants also took significantly less time to memorise a target in the visual search task. However, such an effect of urban outdoor noise condition was not observed. In addition, neither of urban indoor and outdoor noise conditions did not have an effect on visual search time. Nevertheless, we observed a negative effect of urban outdoor noise on the text entry task, as the time per character entry was significantly longer as compared to the silent condition. These findings can be explained by the distracting nature of urban noise [19]; in order to escape these unpleasant conditions participants were quicker to complete these tasks. Moreover, as the outdoor urban noise increases cognitive load [18], it affected participants' performance during the text entry task; hence, they required more time to concentrate to type the text. This finding was also confirmed with the qualitative data. The majority of the participants (13 out of 24) mentioned that they were *"distracted"* and *"annoyed"* by the urban noise conditions and could not concentrate on the smartphone tasks. In fact, the participants mentioned that their perceived performance in both the visual search and text entry tasks was negatively affected by the urban noise conditions; hence, supporting our quantitative findings.

Finally, we demonstrate that the effects of speech were limited to the text entry task; but neither the target acquisition nor the visual search tasks. In particular, we show that when listening to the meaningful speech (*i.e.,* English), participants took significantly longer time per character entry compared to the silent condition. This is due to the distracting nature of meaningful speech [19] and its negative effect on cognitive performance [17,261]. As the text entry task involves cognitive abilities of people [229], it was affected by the additional load caused by the meaningful speech. Interestingly, meaningless speech did not have a significant effect on the text entry performance, which shows that participants could ignore the presence of the meaningless speech due to their inability to understand the language presented in this condition (*i.e.,* Kazakh). Quantitative data conforms with the qualitative findings from the study. Our participants (13 out 24) mentioned that meaningful speech was distracting them, hence it was more difficult to focus on the text entry task. In addition, our participants mentioned that the meaningful speech also affected their performance on the visual search task. However, our quantitative data did not support this statement.

9.1.2 Stress

Chapter 5 presents our findings on the effects of stress on mobile interaction performance. Our results show that stress negatively affected the target acquisition task; however, its' negative effect on the visual search and the text entry task was not observed. We demonstrate that participants took significantly less time to tap targets, and their accuracy was significantly lower when they were experiencing stress. These findings are in line with literature that demonstrates that under stress people tend to rush through their tasks and in general have higher error rates due to anxiety [163].

Qualitative data from this study shows that stress affected not only participants mobile interaction performance, but also physical and emotional well-being. The majority of the participants stated that they were more jittery when experiencing stress. This might have been a reason for reduced accuracy in the target acquisition task. Moreover, the majority of our participants (19 out of 24) said they wanted to complete the smartphone tasks as soon as possible as they did not feel comfortable and wanted to "escape" the situation. This also contributed to their reduced accuracy in the target acquisition task, even though we did not observe a significant negative effect of stress on the visual search and text entry tasks.

9.1.3 Dim Ambient Light

Chapter 6 presents our results on the effects of dim ambient light on mobile interaction performance. Our study shows that dim light has a negative effect on the target acquisition task as it increases the target access time and increases the touch offset size as compared to the normal light condition. This effect of dim ambient light might be due to the decreased colour-differentiation abilities [220] and increased difficulty to see the content of the screen in dark environments [77]. Chapter 6 further demonstrates that wearing sunglasses had a negative effect on the visual search task, as the participants were significantly slower memorising a target icon when compared to a normal light condition. Previous work has shown that low illuminance decreases search speed in reading task [139], hence as sunglasses dim vision perception, our results agree with previous work [139].

Qualitative data of this study shows that participants (8 out of 28) felt the negative effect of dim ambient light and wearing sunglasses on their perceived smartphone interaction performance in the target acquisition task as they mentioned they took longer time and were less accurate to tap the targets under dim light and when wearing sunglasses. This statement is in line with our quantitative data. Interestingly enough, the majority of our participants (17 out of 28) did not feel the negative effect of dim ambient light on their time to memorise a target icon in the visual search task, even though our quantitative data shows the opposite of this statement, as we found that while wearing sunglasses participants took significantly longer time to memorise an icon. Furthermore, the participants mentioned that it was difficult to find target icons (10 our out 28) and type the text (8 out of 28) under the dim light and when wearing sunglasses. Nevertheless, these statements were not supported via our quantitative data and we did not establish the effects of dim ambient light on mobile interaction performance in the visual search and the text entry tasks.

9.1.4 Summary

The above-mentioned studies have quantified the effects of ambient noise, stress, and dim ambient light on mobile interaction performance. Our findings show that there are effects in both directions, *e.g.,* either improving or decreasing performance on mobile interaction and each SIID has an individual effect on each of the smartphone tasks. These effects are summarised in Table 7.1. The effects of SIIDs are different due to several factors including but not limited to the physiological and mental response of the human body to SIIDs. For example, in cold ambience, body temperature drops, including the temperature of the extremities, as it is a natural physiological response [170]. With the drop in temperature, the muscle stiffness grows and the dexterity drops [91]. Hence, cold-induced SIIDs will affect mobile tasks requiring finger dexterity more compared to other SIIDs that do not affect motor performance. Furthermore, we can observe from Table 7.1 that under stress, participants were significantly quicker to complete target access and memorisation in visual search task. This is due to the fact that stress affected our participants mentally and caused anxiety [128], which in its turn decreased task completion time as has been shown in prior research [163]. Having shown the impact of these three SIIDs on different types of mobile tasks, next we discuss how these effects compare to each other.

9.2 RQ2. How do these effects compare to each other?

A significant amount of research has been conducted to investigate the effects of different SIIDs on mobile interaction; however, the majority of the studies were conducted in an ad-hoc fashion and research on SIIDs lacks systematic investigation. This results in the inability to draw fair comparisons between the effects of different SIIDs, and, hence, establish a consensus within the SIIDs research area. Therefore, in order to draw a fair comparison between the effects of different SIIDs on mobile interaction several factors need to be taken into consideration.

First, it is necessary to use identical measure variables to observe the effects of SIIDs on mobile interaction. This can be achieved by using the same tasks across multiple studies and measuring the same variables within the task. For example, this thesis presents how three smartphone tasks: target acquisition, visual search, and text entry were used across the different studies. Despite the difference between the SIIDs, these smartphone tasks measured the effects of the SIIDs on mobile interaction performance in terms of target access time and touch offset size (target acquisition task), memorisation time and visual search time (visual search task), time per character entry and total error rate (text entry task). This consistency among measure variables was the first step to provide a fair comparison between the effects of different SIIDs on mobile interaction performance. In addition, it is necessary to provide the participants with extensive training to avoid any possibility of sequence effects.

Then, there has to be a consistency within the protocol of the studies. Namely, each of the studies require having a baseline condition which allows observing participants' behaviour when SIIDs are not present. This further provides with an opportunity to compare the effects of different SIIDs respective to their baseline. Most importantly, the effects of SIIDs should not be compared directly to each other, but rather indirectly as a percentile difference to the respective baseline. Performing comparison between the SIIDs according to their percentile growth/drop respective to their baseline, reduces the presence of possible bias that can be caused by the variation in the participants sample.

This comparison empowers our understanding in terms of the magnitude of the effects for each SIID, as we can anticipate which SIID has a more prominent effect on mobile interaction performance. This knowledge can then facilitate building appropriate sensing, modelling, and adapting mechanisms to accommodate the effects of SIIDs, perhaps giving a preference to the most prominent one for a given task. Designing mobile technology that addresses user needs appropriate to their contextual factors can improve people's user experience and ensure that they receive procured information in a timely manner [247].

9.3 RQ3. How can mobile devices sense the onset of cold-induced SIIDs?

HCI and UbiComp research has demonstrated that smartphone sensors can be utilised to detect context [2, 56, 240], surrounding environment [198], and activity recognition [8, 252, 265]. We followed a similar approach and used a smartphone sensor to sense cold-induced SIIDs. In particular, Chapter 8 presents our work on how we utilised smartphone's built-in battery sensor to detect if a user is experiencing cold-induced SIIDs.

Our findings demonstrate that smartphone battery temperature highly correlates with participants' finger temperature ($r = 0.86$ and $r = 0.85$ for index finger and thumb respectively). Both smartphone battery temperature and participants' finger temperature dropped in a cold environment and increased in a warm setting. Hence, smartphone battery temperature can be an estimate to user's finger temperature and a drop in temperature can indicate that the user is exposed to cold setting and potentially experiencing cold-induced situational impairments.

The detection mechanism might work in the following way. The device's battery temperature should be registered by the OS at the moment of the first interaction with the device and needs to be recorded at particular time intervals. In case when the consistent temperature drop is observed and reached a specific threshold, the device can adapt the interface to accommodate cold-induced SIIDs and warn the user about possible overexposure to cold temperatures. Moreover, mechanisms to model or predict how a user interacts with their mobile phone and for how long [108, 125, 144, 258] can further assist with effective adaptations.

We also argue that the detection mechanism can be improved if smartphone's battery temperature is used in combination with user input (*e.g.,* performance during target acquisition task). Nevertheless, it is important to account for external factors that might be present during detection time. For example, a user might be wearing capacitive gloves while interacting with the smartphone, hence diminishing the accuracy of detection. However, we argue that a smartphone should be able to distinguish between the interaction of the user when wearing capacitive gloves and when not.

9.4 Future Directions for SIID Research

As Wobbrock *et al.* argue in their work [273], the concept of disability caused by the context is applicable to everyone. Therefore, conducting research on SIIDs can benefit users of all abilities. For example, if technology is designed to be used in a one-handed interaction mode [37, 72] to accommodate SIIDs caused by encumbrance [183, 186], it can also be beneficial for a user who has only one arm.

Within the scope of this thesis, SIIDs such as ambient noise, stress, and dim ambient light have been investigated to quantify their effects on mobile interaction. These SIIDs have been investigated independently and under controlled laboratory settings. These can be limitations of the research conducted in this thesis; however, these experimental designs were necessary for several reasons. First of all, as the effects of the above-mentioned SIIDs have not been established on mobile interaction, it was necessary to exclude any confounding factors that might potentially influence and add to the effects of each of the SIIDs on mobile interaction. Therefore, having strictly controlled laboratory settings helped us to avoid any potential additional factors which would question reliability of our results.

Now that we have established the effects of these SIIDs on mobile interaction, it is time to take the research on SIIDs to the next step. For example, future research could examine the effects of combined situational impairments on mobile interaction, particularly because it is common for users to interact with mobile devices while being exposed to multiple SIIDs, *e.g.,* under bright light while walking on the street in winter in Northern Europe. Furthermore, future research on SIIDs should also be conducted in the wild to maximise the realism of the surrounding context. This could potentially bring new insights to the research agenda as new behaviour of people could be observed under realistic conditions that cannot be observed in laboratory settings.

Furthermore, there are other SIIDs that have been acknowledged and recently summarised [269]. Many of them include but are not limited to behavioural (*e.g.,* operating machinery), environmental (*e.g.,* difficult terrain, confinement, extraneous force), attentional (*e.g.,* diverted gaze, multitasking, distraction), affective (*e.g.,* fatigue, fear, intoxication), social (*e.g.,* laws, crowds, social norms), and technological (*e.g.,* lack of power and/or connectivity) SIIDs and remain underexplored as their effects on mobile interaction is unknown [269]. It is crucial to build a scientific understanding of the underexplored SIIDs, in order to be able to progress further in terms of building sensing, modelling, and adapting mechanisms for these SIIDs [269].

If the effects of underexplored SIIDs (*e.g.,* fear or difficult terrain) on mobile interaction performance are shown to be similar to the ones that have already been studied (*e.g.,* stress), then design guidelines for user interfaces to accommodate explored SIIDs could also be applied to address underexplored SIIDs. Furthermore, as researchers in accessible computing have already emphasised the link between building design solutions for people with disabilities and people in disabling situations [269], the broader knowledge on SIIDs and the ways to accommodate them enables potential solutions for broader range of accessible technology to assist people with permanent disabilities. Furthermore, it might be more beneficial to run lab studies to understand the effects of these aforementioned underexplored SIIDs before conducting in-the-wild studies to avoid exhaustion of resources (*e.g.,* human, financial, technological).

Wobbrock *et al.* defined SIIDs according to a 2D space defined by location and duration [269, 273]. Location SIIDs arise “from within” the user, “from without” the user, and might have a “mixed” nature. “From within” SIIDs are present in almost every context as they arise from user’s internal states, *e.g.,* mood, emotions, being asleep [273]. Meanwhile, “from without” SIIDs are caused by the surrounding context and can be eliminated or reduced, if the context is removed [273]. Finally, as the names speaks for itself, “mixed” SIIDs are caused due to both the context and internal state of the user, *e.g.,* a visually-impaired user interacting with the device under bright light. In terms of duration, Wobbrock *et al.* distinguish ephemeral (short-term and quickly changing, *e.g.,* sleeping, drunkenness) and enduring (long-term or permanent, *e.g.,* blindness, arthritis) SIIDs [273].

Hence, one other potential direction for SIIDs research is to investigate SIIDs according to the above-mentioned 2D space [273]. For example, very few works have looked into the “from within” SIIDs, such as user affect and emotional state, including our work presented in Chapter 5. Several works have looked into emotions and mood during mobile interaction, *e.g.,* [159,164,230,232,262]; however, research has not investigated user mood or emotions from the perspective of situational impairments. For example, Mehrotra *et al.* [164] in their work investigate the relationship between the user emotions and application use behaviour. Similarly, work presented in [232] investigates causal relationship between the applications usage behaviour and user emotions. Nevertheless, the aforementioned papers did not measure the performance during mobile interaction and did not investigate the effects of user's emotional state on mobile interaction. Thus, the effects of "from within" SIIDs on mobile interaction remain as a subject for future investigation.

Another aspect to consider when conducting research on SIIDs is the personal and individualistic characteristics of each user. However, designing and building adaptive interfaces to consider personalised behaviour and design might be costly and resource-consuming [273]. Nevertheless, Gajos *et al.* demonstrate that these challenges are solvable by using optimisation algorithms and formulating cost functions [66]. Hence, adaptive interfaces would record user individualistic preferences and abilities, and consider them in familiar and unfamiliar situations [273]. Moreover, researchers should develop and provide a better understanding and judgement of SIIDs and situations in order to decide if the adaptation should take place at all or simply advise the user not to engage in a certain task when they are situationally-impaired. This is crucially important for situations that might come at a high cost, especially when visual and auditory attention needs to be directed to a task of a greater significance (*e.g.,* interacting with a mobile device while crossing a busy intersection).

Finally, scientists conducting research on SIIDs should expand the research scope outside the context of mobile devices. For example, people might be situationally-impaired when using other technology (*e.g.,* musical instruments [9], smartwatches [263], wearable sensors [264], smartspeakers [93], tabletops [241, 254], tablets [101], public displays [73,74,160], miniaturised NIRS scanners [105, 123] and many others). Therefore, given the prevalence of different technology on the market and its availability to the general population, it is important to improve the accessibility of these devices by studying user experience under different SIIDs.

Chapter 10

Conclusion

This thesis systematically quantifies the effects of situationally-induced impairments and disabilities, namely ambient noise, stress, and dim ambient light on mobile interaction through common mobile tasks: target acquisition, visual search, and text entry. This thesis also offers a mechanism for sensing cold-induced situational impairments. The results of the studies presented in this thesis demonstrate that different types of ambient noise affect human performance on different smartphone tasks. For example, music shortens the target acquisition time, while decreases the target acquisition accuracy. Similar to music, urban noise decreases the target access time; however does not influence the accuracy of target acquisition. Nevertheless, urban noise decreases the target memorisation time – an aspect of the visual search task, as well as increases time per character entry in the text entry task. Furthermore, meaningful speech similar to urban noise negatively affects text entry as it prolongs the time per character entry. The effects of internal factor – stress – was also measured on mobile interaction performance. Our findings show that stress shortens the target access time, however increases the touch offset size, hence deteriorates the accuracy of touch. Finally, we also studied the effects of dim ambient light and report that under dim ambient light target access time increases while the accuracy of touch drops as well as the target memorisation time increases.

Furthermore, this thesis presents a methodology that enables a fair comparison of the magnitude of the effects of different SIIDs on mobile interaction. First, we recommend using the similar variables that quantify mobile interaction performance under different SIIDs to measure their effect. Second, it is important for each of the experiment to contain a baseline condition to record mobile interaction performance without the influence of SIIDs. Finally, when comparing the effects of different SIIDs to each other, it is necessary to compare a percentage growth/drop in performance respective to the baseline condition, rather than manipulating direct comparisons between the effects.

We then recommend using smartphone's battery temperature for sensing cold-induced SIIDs. We demonstrate that smartphone battery temperature correlates highly with human finger temperature in cold and warm environments. We advocate that our method is applicable during continuous interaction with the device and enables off-the-shelf smartphones to sense cold-induced SIIDs. Hence, being aware of this information, off-the-shelf smartphones can then adapt the interface accordingly to accommodate the effects of cold-induced SIIDs.

In addition, we argue that providing a systematic understanding of the effects of underexplored SIIDs is the pillar of SIIDs research agenda. Better understanding of the effects of different SIIDs enables further construction of sensing mechanisms, creation of techniques to model SIIDs and user behaviour under SIIDs, as well as interface adaptation to accommodate for SIIDs. We foresee that future directions for SIIDs research should focus on studying the effects of combined SIIDs and SIIDs that come "from within" the user (*e.g.,* emotions). Furthermore, the scope of SIIDs research should be extended outside mobile devices by considering their effects on other technology (*e.g.,* smartwatches, smartspeakers). Finally, a user's personal and individualistic characteristics should be considered when conducting future research on SIIDs.

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Title:
Quantifying the Effects of Situationally-Induced Impairments and Disabilities on Mobile Interaction

Date:
2020

Persistent Link:
http://hdl.handle.net/11343/239076

File Description:
Final thesis file