Understanding Age-related Selection Difficulties with Touch Input

Afroza Sultana

School of Information Studies

McGill University

Montreal, Canada

April 2022

A thesis submitted to McGill University in partial fulfilment of the requirements for the degree of Doctor of Philosophy.

Abstract

Age-related declines in physical and cognitive function can result in target selection difficulties (i.e., difficulties with selecting a button or a link) with a mouse, pen, or a touch input device. This shift over the lifespan can hinder device operation, particularly in older adults. Previous studies have detailed the different types of target selection errors encountered, as well as how they vary with age and with input devices for mouse and pen interaction. Another branch of prior studies dedicated their focus on understanding selection difficulties through mouse and pen input device trajectory analysis. This thesis aims to understand age-related selection difficulties that are encountered with touch input devices, and expands upon prior works on error analysis and input device trajectory analysis.

The thesis presents three studies conducted within controlled laboratory experiments. The first study described the types of age-related selection errors encountered with touchscreen devices. Consistent with prior results from mouse and pen input studies, older adults had longer target selection times, generated higher error rates, and encountered a broader range of selection errors (i.e., misses and slips), relative to a younger comparison group. Among these two types of errors, miss errors were a more common source of errors in older adults than slip errors. These findings also highlighted the differences in errors encountered by older adults between pen and touch input, and stressed the need to consider pen and touch interaction separately, despite both being forms of direct interaction.

The second study laid the groundwork for touch input trajectory analysis. To date, tra-

jectory analysis has only been conducted on two-dimensional cursor trajectories from mouse and pen input devices. We introduced sixteen three-dimensional touch input trajectory analysis measures by combining and extending prior two-dimensional measures. These measures were designed to reflect on selection difficulties, such as overshoots, undershoots, corrective submovements, deviation from the ideal selection path, pauses, finger velocity, and twisting of the finger during target selection. We examined the reliability of these measures by demonstrating their impact on overall low performance throughput with touch input. Our study found strong associations between higher counts in finger direction changes, longer trajectory paths, higher counts in long pauses throughout the trajectory, and lower performance throughput. These findings confirmed that these new three-dimensional measures can provide more nuanced insight on the reasons behind having lower performance throughput in touch input. Moreover, such analysis can be further applied to understand age-related selection difficulties with touch interaction.

The third study applied the three-dimensional trajectory analysis measures to decode age-related performance differences with touch input. Our study results demonstrated that older adults need to take smaller corrective submovements all over the selection trajectory because of experiencing higher counts of overshoots and undershoots, higher deviation from the ideal selection path, and sudden high finger velocity. These selection behaviours also reduce their overall performance throughput, compared to younger adults. The relationship between the finger trajectory measures and lower throughput is significantly influenced by age. While the above-mentioned measures, along with frequent long pauses affected the throughput for older adults, throughput for younger adults was only affected by frequent long pauses.

In summary, this thesis identified age-related selection difficulties that might be precluding older adults from enjoying the full benefits of modern touchscreen technologies. Our insights can point towards potential design solutions for better accessible touchscreen interfaces for older adults. For example, designing larger targets, exploring selection techniques, such as zooming and mid-air pointing, and providing feedback to stay close to the ideal selection path. Our work can be further extended to understand touch selection difficulties with different task scenarios, form factors, and populations. The contributions of this thesis also have potential application for creating standards for measuring selection performance of touch interaction and designing ability-based touchscreen interfaces that will considerably benefit accessibility related research areas.

Résumé

Les déclins des fonctions physiques et cognitives liés à l'âge peuvent entraîner des difficultés de sélection de la cible (c'est-à-dire des difficultés à sélectionner un bouton ou un lien) avec une souris, un stylet ou un périphérique de saisie tactile. Ce changement au cours de la vie peut entraver le fonctionnement de l'appareil, en particulier chez les personnes âgées. Des études antérieures ont détaillé les différents types d'erreurs de sélection de cibles rencontrées, ainsi que leur variation avec l'âge et avec les périphériques d'entrée pour l'interaction de la souris et du stylet. Une autre branche d'études antérieures s'est concentrée sur la compréhension des difficultés de sélection a cause de l'analyse de trajectoire de périphérique d'entrée de souris et de stylet. Cette thèse vise à comprendre les difficultés de sélection liées à l'âge rencontrées avec les périphériques de saisie tactiles et à développer les travaux antérieurs sur l'analyse des erreurs et l'analyse de la trajectoire des périphériques de saisie.

La thèse présente trois études menées a l'expériences contrôlées en laboratoire. La première étude décrit les types d'erreurs de sélection liées à l'âge rencontrées avec les appareils à écran tactile. Conformément aux résultats antérieurs d'études de saisie à la souris et au stylet, les personnes âgées ont consommé plus du temps pour sélectionner des cibles, généraient des taux d'erreur plus élevés et rencontraient un plus large éventail d'erreurs de sélection (les erreurs ratée et les erreurs de glissement). Parmi ces deux types d'erreurs, les erreurs ratée étaient une source d'erreurs plus fréquente chez les personnes âgées que

les erreurs de glissement. Ces résultats ont également mis en évidence les différents erreurs rencontrées par les personnes âgées entre la saisie au stylet et la saisie tactile, et ont souligné la nécessité de considérer séparément l'interaction du stylet et du toucher, bien que les deux soient des formes d'interaction directe.

La deuxième étude a jeté les bases d'analyse trajectoire d'entrée tactile. À ce jour, l'analyse trajectoire n'été pas menée que sur des trajectoires de curseur bidimensionnelles à partir de périphériques de saisie de souris et de stylet. Nous avons introduit seize mesures d'analyse de trajectoire d'entrée tactile tridimensionnelles en combinant et en étendant des mesures bidimensionnelles antérieures. Ces mesures ont été conçues pour refléter les difficultés de sélection, telles que les dépassements, les sous-dépassements, les sous-mouvements correctifs, les écarts par rapport au chemin de sélection idéal, les pauses, la vitesse du doigt et la torsion du doigt lors de la sélection de la cible. Nous avons examiné la fiabilité de ces mesures en démontrant leur impact sur le débit global à faible performance avec la saisie tactile. Notre étude a révélé de fortes associations entre des nombres plus élevés dans les changements de direction des doigts, des chemins de trajectoire plus longs, des nombres plus élevés dans les longues pauses tout au long de la trajectoire et un débit de performance inférieur. Ces résultats ont confirmé que ces nouvelles mesures tridimensionnelles peuvent fournir des informations plus nuancées sur les raisons d'un débit de performance inférieur dans la saisie tactile. De plus, une telle analyse peut être davantage appliquée pour comprendre les difficultés de sélection liées à l'âge avec l'interaction tactile.

La troisième étude a appliqué les mesures d'analyse de trajectoire tridimensionnelle pour décoder les différences de performances liées à l'âge avec la saisie tactile. Les résultats de notre étude ont démontré que les personnes âgées doivent effectuer des sous-mouvements correctifs plus petits tout au long de la trajectoire de sélection en raison du nombre plus élevé de dépassements et de sous-dépassements, d'un écart plus important par rapport au chemin de sélection idéal et d'une vélocité soudaine des doigts. Ces comportements de sélection réduisent également leur rendement global par rapport aux jeunes adultes. La relation entre les mesures de la trajectoire des doigts et le débit inférieur est significativement influencée par l'âge. Alors que les mesures mentionnées ci-dessus, ainsi que les longues pauses fréquentes ont affecté le débit pour les personnes âgées, le débit pour les jeunes adultes n'a été affecté que par de longues pauses fréquentes.

En résumé, cette thèse a identifié les difficultés de sélection liées à l'âge avec les technologies d'écran tactile modernes. Nos connaissances peuvent orienter vers des solutions de conception potentielles pour des interfaces à écran tactile plus accessibles pour les personnes âgées. Par exemple, concevoir des cibles plus grandes, explorer des techniques de sélection, telles que le zoom et le pointage a l'air, et fournir des commentaires pour rester proche du chemin de sélection idéal. Notre travail peut être étendu pour comprendre les difficultés de sélection tactile avec différents scénarios de tâches, facteurs de forme et populations. Les contributions de cette thèse ont également une application potentielle pour créer des normes de mesure des performances de sélection de l'interaction tactile et concevoir des interfaces à écran tactile basées sur les capacités qui bénéficieront considérablement aux domaines de recherche liés à l'accessibilité.

Acknowledgments

I would like to thank everyone who supported me in this doctoral journey. First and foremost, I would like to express my deepest gratitude to my supervisor Prof. Karyn Moffatt. This thesis would not have been possible without her valuable guidance, endless encouragement, and continuous support in every step of my doctoral studies. I deeply value the academic and professional mentorship she offered me over these years. I also want to thank the members of my doctoral committee Prof. Benjamin Fung and Prof. Jamshid Beheshti for providing me with valuable input and guidance on my research.

I extend my thanks to the faculty members of McGill School of Information Studies (SIS). I am especially grateful to the current and former Directors of SIS, Prof. Kimiz Dalkir and Prof. France Bouthillier, and the Graduate Program Director Prof. Joan Bartlett for their guidance and support. I also would like to thank Administrative and Student Affairs Coordinator Ms. Kathryn Hubbard and Administrative Officers Ms. Cathy (Caterina) Venetico and Ms. Shannon Sullivan for providing me with various forms of administrative support, whenever I needed them.

This work was supported by scholarships from Fonds de Recherche du Quebec–Nature et Technologies (FRQNT) Bourses de doctorat en recherché, Graphics, Animation and New Media (GRAND) NCE[1] Postgraduate Scholar Program, McGill SIS Graduate Excellence Award, and McGill SIS Grad Travel Award, as well as grants from Natural Sciences and En-

[1]NCE refers to Networks of Centres of Excellence program.

gineering Research Council of Canada (NSERC) [418290-2012-RGPIN, RGPIN-2018-06130], Fonds de Recherche du Quebec–Nature et Technologies (FRQNT) [2013-NC-164701], Canada Research Chairs Program (CRC), Aging Gracefully across Environment using Technology to Support Wellness, Engagement, and Long Life (AGE-WELL) NCE Inc. as part of the CONNECT-CREATE project, and Graphics, Animation and New Media (GRAND) NCE as part of the INCLUDE project. I would like to thank all the above funding agencies as well as McGill School of Information Studies (SIS) for their generous financial support to carry on this research.

I want to convey my gratitude to Prof. Jeremy Cooperstock, Prof. Benjamin Fung, and CCS Collective Community Services for providing me with space to run my studies. I am grateful to all organizations that allowed me to speak with their members and helped me to circulate the call for participation posters and flyers. Without their generous help, it would be very difficult to reach out to older adult participants. I am also thankful to my study participants for their time and effort.

I wish to thank all of my current and former colleagues from the Accessible Computing Technologies (ACT) Research Lab for creating a very supportive and vibrant work environment. Special thanks go to Robert, Daniele, Mauricio, Jiamin (Carrie), Muhe, Amira, Carolyn, and Taciana for always being very generous with their time to provide continuous feedback on my work, form the very beginning of my research to the complete thesis draft. Their constructive feedback and suggestions over the years have significantly improved this thesis. I wish to thank Amira for proofreading the french abstract of the thesis, and Mauricio, Carrie, and Muhe for proofreading different chapters of this thesis. I want to thank Mitacs Globalink Summer Research Interns Ms. Jiamin He and Ms. Jinqing Xu for their contributions on developing the finger trajectory data collection tool. I also wish to thank my fellow doctoral students from School of Information Studies (SIS), especially, my office mates Daniele and Philips for their support and friendship, and for creating a sense of community within the department.

I wish to thank all of my friends who created a home away from home for me in Montreal. I also want to thank my friends who were not here with me, but always kept in touch with me and encouraged me in this entire process. This thesis was written when the whole world was shut down due to a global pandemic. Without the continuous support from my friends, both home and abroad, it would be impossible to carry on in such a difficult time.

Most importantly I would like to express my deepest gratitude to my parents and my siblings Nargis, Sabbir, and Ishrat. They have always encouraged me to pursue my doctoral studies. I cannot thank them enough for their unconditional love and support throughout this long journey. They have always believed in me, even when I doubted myself. I also want to thank my nephew Shadman, nieces Anika and Aisha, cousins, uncles, aunts, and all members of my extended family. Last but not the least, I want to thank my late grandmother who taught me the value of education and hard work.

Dedication

This thesis is dedicated to

My nanu (grandmother) Late Meherunnesa Islam

And

My nephew Shadman, and nieces Anika and Aisha

Contents

List of Figures

List of Tables

List of Acronyms

A	Target Amplitude
DSST	Digit Symbol Substitution Test
DC-X	Movement Direction Change along the X-Axis
DC-Y	Movement Direction Change along the Y-Axis
DC-Z	Movement Direction Change along the Z-Axis
ID	Index of Difficulty
IP	Index of Performance
LST	Letter Set Test
MDC	Movement Direction Change
ME	Movement Error
MO	Movement Offset
MV	Movement Variability
NAART	North American Adult Reading Test
OA	Older Adults
ODC	Orthogonal Direction Change
PAR	Path Axis Ratio
PD	Pause Duration
PF	Pause Frequency
PLD	Pause Location Distance
RP	Mean Pitch (Rotation)

RR	Mean Roll (Rotation)
RY	Mean Yaw (Rotation)
SM	Mean Speed
SP	Peak Speed
TAC	Task Axis Crossing
TP	Performance Throughput
TPC	Task Plane Crossing
TRE	Target Re-Entry
W	Target Width
W_e	Effective Target Width
YA	Younger Adults

Chapter 1

Introduction

1.1 Thesis Motivation

Adults, aged 65 years and older, comprise one of the fastest growing populations in the world, particularly, in developed countries. Modern handheld touchscreen technologies (e.g., smartphones and tablets) can provide useful applications, such as, health information monitors, social networks, news portals, maps, location trackers, and games – that can improve the quality of lives of older adults (Alam et al., 2012; Cash, 2003; Dickinson & Hill, 2007; Massimi et al., 2007; Moffatt et al., 2013; Nischelwitzer et al., 2007; Robinson et al., 2009; Topo, 2009). In 2017, Pew Research Center conducted a survey on older adults who were residing in the U.S.A and found that older adults in recent time are more interested in using handheld touchscreen technologies than their counterparts from even a few years ago (Anderson & Perrin, 2019). In that survey, forty-two percent of older adults reported owning a smartphone, and thirty-two percent, a tablet, up from eighteen percent each in 2013. Respondents reported to be actively engaged with their devices, with roughly three-quarters reporting daily use of internet. The increasing adoption of touchscreen devices among older adults is not entirely surprising. Prior studies have categorized direct interaction (both pen and touch[1]) to be a more accessible option for older adults, relative to any indirect input devices, such as, mouse, and trackball, due to its better support for hand-eye coordination (Charness et al., 2004; Findlater et al., 2013; Kim et al., 2020; Schneider et al., 2008).

Despite this potential, age-related physical, cognitive, and sensory declines in many older adults continue to pose barriers to the usage of touchscreen technologies. Prior studies reported selection difficulties among older adults, while selecting targets (i.e., a selectable item, for example, a button or an icon) with both pen input devices (Hourcade & Berkel, 2007; Ketcham et al., 2002; Moffatt & McGrenere, 2007; Sultana & Moffatt, 2013) and touch input devices (Findlater et al., 2013; Gao & Sun, 2015; Massimi et al., 2007; Motti et al., 2013; Rogers et al., 2005). These selection difficulties can hinder adoption of touchscreen technologies in older adults, as acceptance of a new technology is influenced by both need and accessibility (McCreadie & Tinker, 2005).

A popular trend in accessibility related research is to develop new interaction techniques to overcome selection difficulties. However, some prior studies have emphasized the importance of understanding the reasons behind selection difficulties before designing new accessi-

[1] In this thesis, we use the term touch interaction to specifically refer to touch interaction using the tip of the finger, and pen interaction where an intermediary device such as a pen or stylus is used.

ble techniques (Hwang et al., 2005; Keates & Trewin, 2005; MacKenzie et al., 2001; Moffatt & McGrenere, 2007). Moffatt and McGrenere (2007) criticized reporting the effectiveness of the new techniques only in terms of gross measures like speed (selection time) and accuracy (error rate), while being unable to draw valuable insight on the limitations (such as lack of affordance, or additional accessibility challenges) from any inconclusive results. MacKenzie et al. (2001) also echoed similar concerns about not prioritizing on understanding selection difficulties, and pointed out that speed and accuracy measures alone can provide limited information about selection performance.

To understand target selection difficulties with both direct and indirect input devices, some prior works, though limited, demonstrated the usefulness of target selection error analysis (Keates & Trewin, 2005; Moffatt & McGrenere, 2007) and target selection trajectory analysis (Hwang et al., 2005; Ketcham et al., 2002; MacKenzie et al., 2001; Wobbrock & Gajos, 2008). Selection error analysis studies on mouse (Keates & Trewin, 2005) and pen (Moffatt & McGrenere, 2007) interaction have identified the most common types of selection errors among older adults. Furthermore, these studies inspired future researchers to design novel interaction techniques, such as, steady clicks (Trewin et al., 2006) and steadied-bubble (Moffatt & McGrenere, 2010) that reduced age-related selection errors with mouse and pen input, respectively. Selection trajectory analysis studies on mouse (Keates & Trewin, 2005) and pen (Ketcham et al., 2002) input identified a number of selection behaviors in older adults (e.g., too much deviation from the ideal selection path, too many direction changes, etc.) that are strongly associated with low performance throughput. Selection trajectory studies on motor impaired individuals (Hwang et al., 2005) inspired accessible selection techniques, such as, gravity well (Hwang et al., 2003) and haptic tunnel (Langdon et al., 2002). Despite prior error analysis and trajectory analysis studies on mouse and pen interaction provided additional understanding on age-related selection difficulties, similar studies have not been conducted for touch interaction. This thesis addresses this gap in the literature by conducting error analysis and trajectory analysis studies for touch input – in order to gain a deeper understanding on target selection difficulties of older adults with touchscreen device interaction.

1.2 Thesis Goals and Overview

The overall goal of this thesis is to understand age-related target selection difficulties with touch input by extending prior works on selection error analysis and selection trajectory analysis with mouse and pen input. In particular, we answer the following three research questions (*RQs*) in this thesis:

RQ1:

> *RQ1.1. What types of selection errors are encountered by older adults with touch input?*
>
> *RQ1.2. Among all types of selection errors encountered by older adults, which one is the most predominant error?*

RQ2:

RQ2.1. What is the relationship between each of the three-dimensional finger trajectory analysis measures[2] *and performance throughput for touch input?*

RQ2.2 How do these finger trajectory analysis measures relate to each other?

RQ3:

RQ3.1. How can the finger trajectory analysis measures be used to characterize age-related performance differences?

RQ3.2. How does age influence the relationships and dependencies between the finger trajectory analysis measures and performance throughput?

The following subsections elaborate on each of these research questions, and describe how this thesis answers them.

1.2.1 RQ1: Error Analysis

The first research question (*RQ1*) focuses on understanding age-related selection difficulties through analyzing selection errors, encountered by older adults. We answer the following two sub-questions under *RQ1*:

RQ1.1. What types of selection errors are encountered by older adults with touch input?

[2] In this thesis, we use the term *finger trajectory* to refer to *touch input trajectory*. Three-dimensional finger trajectory analysis measures are introduced in Section 4.2.

RQ1.2. Among all types of selection errors encountered by older adults, which one is the most predominant error?

We conducted a controlled laboratory study with 20 older adults and 16 younger adults to answer *RQ1.1* and *RQ1.2*[3]. Younger adults were included in this study to identify the performance differences across age groups. Participants were asked to complete a Fitts's task-like two-dimensional target selection task (Fitts, 1954; MacKenzie, 1992; Ren & Moriya, 2000) with targets that are comparable in size to those of selectable items on popular smartphones and tablets (i.e., between 4.88 mm to 9.22 mm). First, we provided detailed analysis on the overall performance differences across age groups in terms of selection time, error rate, number of corrective attempts, finger pressure, and selection endpoint variability. Next, we emphasized on understanding selection errors with touch input. Prior studies have detailed the different types of target selection errors encountered, as well as, how they vary with age, and with input device for mouse (Keates & Trewin, 2005) and pen interaction (Moffatt & McGrenere, 2007). We extended these works in our error analysis study to categorize age-related selection errors with touch interaction. Consistent with prior results, we found that older adults had longer target selection times, generated higher error rates, required higher number of corrective attempts to recover from an error, added more finger pressure on the screen for target selection, and had higher selection endpoint variability. Very high error rates were observed in older adults with small targets that were roughly the size of common selectable menu items in smartphones. Aging influenced both missing the targets

[3]Results of this study are published in Sultana and Moffatt (2017, 2019).

(i.e., selecting outside the targets boundary) and slipping off the targets (i.e., finger landing on the targets, but slipping off before the final selection). Between these two types of errors, missing the targets were more prevalent than slipping off the targets, among older adults. This study also highlighted that although both pen and touch are direct forms of interaction, age-related selection difficulties vary between these two input devices.

1.2.2 RQ2: Finger Trajectory Analysis Measures

Extending the prior works on trajectory analysis for touch input was not as straight forward as extending the prior works on error analysis. Trajectory analysis studies to date have focused on the two-dimensional path of the mouse cursor within the device screen (Hwang et al., 2005; Keates & Trewin, 2005; MacKenzie et al., 2001), whereas in touch input, the finger moves beyond the device screen and forms a three-dimensional trajectory. To fully understand the three-dimensional properties of touch input trajectories, we extended these prior two-dimensional measures to three-dimensional trajectory measures. Before applying these new trajectory measures to understand age-related selection difficulties, we needed to ensure that these measures can reflect on low performance throughput of touch input, as the prior two-dimensional trajectory measures did for mouse input (MacKenzie et al., 2001). In the second research question (*RQ2*), we examined the associations between the touch trajectory measures (also referred to as finger trajectory measures) and performance throughput.

RQ2.1. What is the relationship between each of the three-dimensional finger *trajectory analysis measures and performance throughput for touch input?*

RQ2.2 How do these finger trajectory analysis measures relate to each other?

We conducted a similar controlled laboratory study as our error analysis study (from *RQ1*) with 16 older adults and 16 younger adults. We custom-built a finger trajectory data collection tool by augmenting a touchscreen tablet with an external motion-sensing device, as no such data collection tool was commercially available[4]. Our study results demonstrated that higher counts in direction changes along all axes, longer trajectory paths, and long frequent pauses throughout the trajectory were strongly associated with lower performance throughput in touch input. Higher values in all of these trajectory measures were possibly caused by too many corrective submovements during a selection task, and higher deviation from the ideal selection path. We also observed three clusters of trajectory measures with strong interdependencies. Findings of this study underlined that three-dimensional finger trajectory measures can provide an additional lens on understanding selection difficulties with touch input, besides measuring the overall selection time, error rates, and throughput.

1.2.3 RQ3: Finger Trajectory Analysis

The third research question (*RQ3*) investigates age-related selection difficulties with touch input through selection trajectory analysis. The following two questions were answered under *RQ3*:

[4]Description of this three-dimensional finger trajectory data collection tool appeared as: Sultana, Xu, and Moffatt (2018).

RQ3.1. How can the finger trajectory analysis measures be used to characterize age-related performance differences?

RQ3.2. How does age influence the relationships and dependencies between the finger trajectory analysis measures and performance throughput?

To answer these questions, we used the same dataset from the study that was conducted to answer *RQ2*. We extended the prior works on mouse and pen input trajectory analyses (Hwang et al., 2005; Ketcham et al., 2002; MacKenzie et al., 2001; Wobbrock & Gajos, 2008) and provided a detailed analysis on the new finger trajectory measures, across age groups. Our analysis identified significant performance differences between older and younger adults, in a subset of the trajectory measures. In particular, older adults frequently changed their finger directions and finger rotations along the selection trajectory. They also travelled longer paths, had more variations in the trajectory, and generated higher peak speed. Besides taking verification pauses near the target boundaries, older adults took frequent pauses throughout the selection trajectory. These findings suggest that older adults substantially deviated from the ideal selection path and needed to take a number of smaller corrective submovements all over the trajectory to reach the targets. Higher values in these trajectory measures also influenced lower performance throughput in this age group.

In summary, this thesis identified a number of selection difficulties with touch input that are encountered by older adults. Having deeper understanding of such age-related selection difficulties are crucial for designing accessible touchscreen interfaces for older adults. The three-dimensional finger trajectory measures, introduced in this thesis, can be applied as additional measures to evaluate touch input performance. Finger trajectory data collection tools similar to the one we built to answer *RQ2* and *RQ3* can be useful in other research areas in HCI that involve touch interaction and mid-air interaction. This thesis also can be extended to performance evaluation for other accessibility related research, involving different population (e.g., individuals with motor impairment), task scenarios (e.g., menu selection), and form factors (e.g., ATM machines). Accessibility related research areas, such as ability-based design can be greatly benefited from the insight gathered by this thesis.

1.3 Thesis Outline

In Chapter 2, we present the related work for this thesis. We first describe the performance evaluation measures for both direct and indirect inputs. Then, we discuss the age-related selection difficulties that were documented by prior studies, followed by performance analysis measures that were applied to identify such difficulties. We present our error analysis study across age groups to answer *RQ1* in Chapter 3. Chapter 4 presents the new three-dimensional touch input trajectory measures. We also answer *RQ2* in this chapter, by demonstrating the relationships and dependencies between these measures and performance throughput. In Chapter 5, we present the trajectory analysis study across age groups and answer *RQ3*. We summarize the findings and contributions from this thesis in Chapter 6, along with the future directions of this thesis that can further benefit older adults with handheld touchscreen devices. We also added appendices in this thesis that contain additional material that are relevant to this thesis. Appendix A includes the data collection forms that were used in the studies from Chapters 3 - 5. Appendix B presents the results of inferential statistical analysis from the error analysis study (from Chapter 3), followed by histograms of error distribution across target widths. Additional statistical analysis results from the trajectory analysis study (from Chapter 5) are presented in Appendix C. A list of publications from this thesis is included in Appendix D. Appendix E contains the ethics approval certificates from McGill University Research and Ethics Board (REB).

Chapter 2

Related Work

2.1 Context

In this chapter, we present prior studies that are relevant to target selection performance evaluation, and selection performance differences across age groups. In Section 2.2, we provide a brief overview on the models that were developed and subsequently evolved to evaluate target selection task performance with both direct and indirect input devices. In Section 2.3, we discuss the effects of physical, cognitive, and sensory declines in individuals due to aging that instigate performance differences in their target selection behaviour, relative to the non-impaired younger individuals. In Section 2.4, we present the body of work dedicated to understand the age-related performance differences on selection tasks. In Section 2.4.1, we discuss the age-related performance differences in terms of the number, types, and prevalence of target selection errors. In Section 2.4.2, we present the age-related performance differences that are reflected on the target selection trajectories of the input devices. Our review on the existing literature reveal that a majority of prior studies on both overall performance evaluation and identifying age-related performance differences were targeted toward indirect input devices, such as, mouse. A limited number of such studies focused on pen interaction. However, studies on performance evaluation, particularly, age-related performance differences with touch interaction, are underrepresented in this body of literature, leaving a number of questions on target selection performance with touch input, unanswered.

2.2 Target Selection Performance Analysis

2.2.1 Fitts's Law and Variants

Target selection performance evaluation studies have heavily relied on Fitts's model (Fitts, 1954), which explains the speed-accuracy tradeoff of rapid and aimed target selection tasks, in relation to the size of and distance to the target (MacKenzie, 1992). More precisely, Fitts's model suggests that larger targets over smaller distances are easier to select (i.e., having lower index of difficulty (ID)), than smaller targets located far apart (see Eq. 2.1). In Eq. 2.1, ID is Index of difficulty, D is target amplitude (also commonly known as target distance), and W is target width (see Figure 2.1). Fitts's model explains the speed-accuracy tradeoff of rapid and aimed target selection tasks (Accot & Zhai, 1997), and observed a strong correlation between task completion time (more commonly known as movement time (MT)) and the index of difficulty (ID) of the selection tasks (see Eq. 2.2, where a and b are constants that depend on individual motor ability and target selection device). The performance of the selection task is measured with the throughput value or index of performance (IP) – the ratio of index of difficulty and the movement time, as shown in Eq. 2.3.

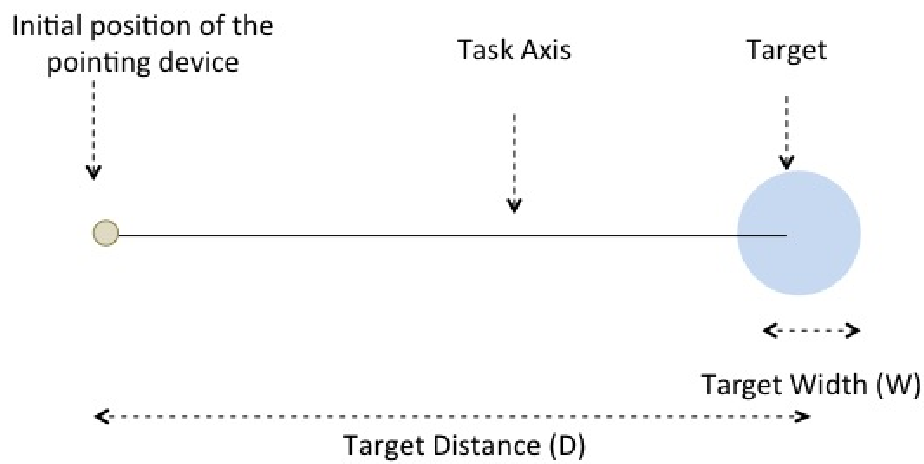


Figure 2.1 Two dimensional target selection task.

$$ID = log_2[\frac{D}{W} + 1] \tag{2.1}$$

$$MT = a + b * ID \tag{2.2}$$

$$IP = ID/MT \tag{2.3}$$

Since Card et al. (1978) applied Fitts's model to evaluate performance of mouse and isometric joysticks, a number of performance evaluation models have been extended from Fitts's model to achieve better data to model fit for Eq. 2.2 (MacKenzie, 1992; Soukoreff & MacKenzie, 2004). One of the most improved extensions of Fitts's model suggests that while selecting a target, individuals more likely select a position near the edge of the targets to achieve better speed-accuracy measures, rather than selecting the center of the target, as assumed in the original Fitts's model (MacKenzie, 1992). This extended model (Welford, 1968) takes account of the normal distribution of the selection endpoints from a particular individual (denoted by σ in Eq. 2.4) – commonly known as the "effective" width (denoted by $\sqrt{2\pi e}\sigma$ in Eq. 2.4), instead of using the actual target width as shown in Eq. 2.1.

$$ID = log_2[\frac{D}{\sqrt{2\pi e}\sigma} + 1] \tag{2.4}$$

Over the years, Fitts's models and their variants have been applied on performance evaluation for both indirect input devices like mouse, joystick, and trackball, (Accot & Zhai, 2003; Grossman & Balakrishnan, 2005b; Keates & Trewin, 2005; MacKenzie, 1992; MacKenzie & Buxton, 1992; Soukoreff & MacKenzie, 2004), and direct input devices like pen and touch (Bi et al., 2013; Forlines et al., 2007; Sasangohar et al., 2009; Sears & Shneiderman, 1991; Soukoreff & MacKenzie, 2004).

2.2.2 Target Selection Trajectory Analysis

Some prior studies highlighted various limitations of applying only Fitts's model and its variants for evaluating target selection performance. First, these studies argued that the aforementioned gross measures evaluated by Fitts's model (i.e., selection time, index of difficulty, and performance throughput, see Section 2.2.1) generally emphasize selection performance at the target selection endpoints, but not necessarily at the target selection trajectory of the input device, albeit selection trajectory contributes to a major proportion of any selection task (MacKenzie et al., 2001; Mithal & Douglas, 1996).

Second, Fitts's model considers target selection trajectory as a straight line that connects the centers of the start button and the target, also known as the task axis (MacKenzie, 1992; Soukoreff & MacKenzie, 2004). However, in real life, target selection trajectories hardly remain within that straight line. Prior works on human psychomotor behavior models argued that target selection trajectories consist of a series of consecutive smaller submovements, rather than one single straight-line trajectory. Some of these models suggest that the submovements from a target selection trajectory are a series of discrete consecutive attempts to correct a previous failed submovements to reach the target (Crossman & Goodeve, 1983; Keele, 1968). Other models suggest that selection trajectories consist of an initial ballistic movement towards the target, followed by subsequent smaller submovements (Schmidt et al., 1979). The most resent models suggest that target selection trajectories are a combination of an initial ballistic movement, followed by consecutive corrective submovements to reach the target (Meyer et al., 1988; Rosenbaum, 2009). In-depth analysis of target selection trajectories can provide valuable insight on human psychomotor behavior to understand selection task performance (Meyer et al., 1988; Mithal & Douglas, 1996).

Third, in Fitts's model, the movement time (target selection time) is defined as a linear function of the index of difficulty of the selection task, and the index of difficulty is defined as a logarithmic function of target width and amplitude (see Eq. 2.1 and 2.2). Therefore, selection difficulty is portrayed as the speed-accuracy tradeoff of the selection task in terms of only the target widths and the amplitudes (MacKenzie, 1992; Soukoreff & MacKenzie, 2004). However, a limitation of Fitts Law is that it reduces performance to a single measure of throughput, abstracting away detail that is relevant to understanding human motor performance. For example, an individual who moves slowly but precisely due to muscle weakness may have similar throughput to someone who moves quickly but imprecisely due to hand tremor. Design solutions to improve performance for these two individuals would likely be quite different. For example, in supporting mouse input, gravity wells have been shown to help speed movement towards a target (Hwang et al., 2003), while haptic tunnels can help steady imprecise movement (Langdon et al., 2002). Though Fitts Law can help explain why both approaches improve throughput, it cannot on its own tease apart how each technique can serve different needs.

To establish selection trajectory analysis as a viable tool for evaluating target selection performance, MacKenzie et al. (2001) introduced seven new trajectory analysis measures and explored their influence on performance throughput. These new measures quantified the properties of selection trajectory deviation from the task axis (the shortest distance between the cursor starting position and the target center), because MacKenzie et al. (2001) anticipated that such trajectory deviation can translate into lower performance throughput in a target selection task. The seven new measures that were introduced by this study are: target re-entry (TRE), target axis crossing (TAC), movement direction change (MDC), orthogonal direction change (ODC), movement variability (MV), movement error (ME), and movement offset (MO), a subset of which is presented in Figure 2.2, and are described below. All measures are counted per trial.

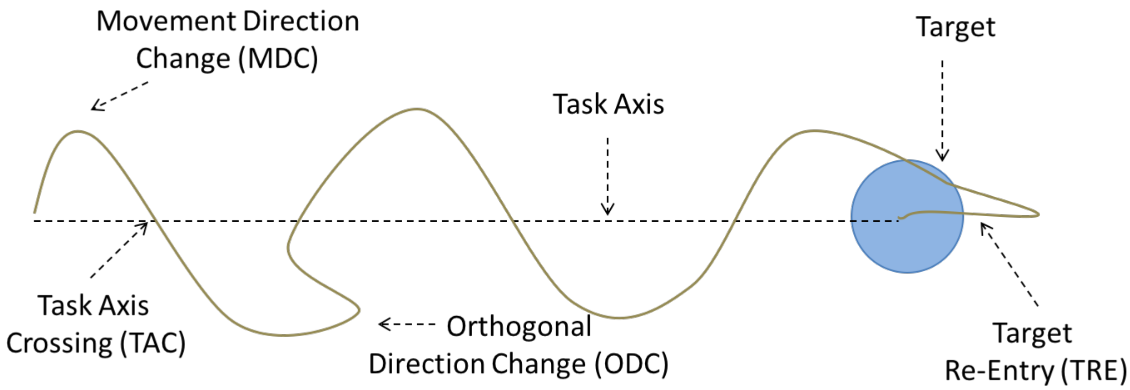


Figure 2.2 A subset of trajectory analysis measures from MacKenzie et al. (2001).

Target Re-Entry (TRE). Target re-entry (TRE) measures the number of times the cursor goes inside the target, before its final selection.

Target Axis Crossing (TAC). The task axis crossing counts the number of times the trajectory crosses the task axis.

Movement Direction Change (MDC). Movement direction change counts the number of times the cursor changes its direction orthogonal to the task axis

Orthogonal Direction Change (ODC). Orthogonal direction change counts the number of times the cursor changes its direction parallel to the task axis.

The rest of the trajectory measures, namely, movement variability (MV), movement error (ME), and movement offset (MO), quantify the deviation of the selection trajectory from the task axis. These measures consider the task axis to be aligned with the x-axis, having the (0, 0) coordinate as the initial cursor position (i.e., the center of the start button). The intermediate data points of the target selection trajectories (shown in Figure 2.3) are represented with $(x_1,\ y_1)$, $(x_2,\ y_2)$, ..., $(x_n,\ y_n)$. The distance between a data point $(x_i,\ y_i)$ and the task axis is denoted with y_i, the mean distance of all intermediate data points from the task axis is denoted with $\overline{y}$, and the number of data points are denoted with n.

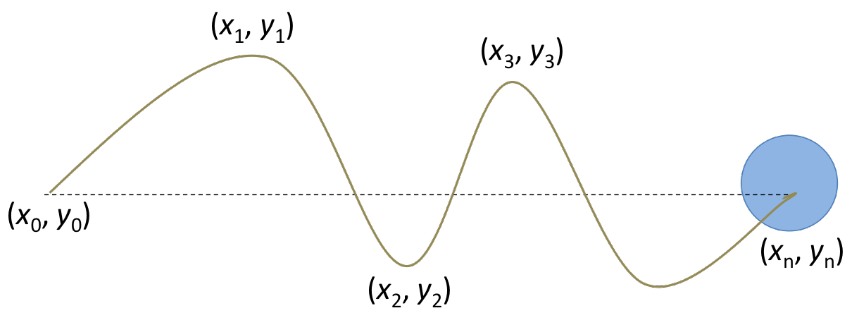


Figure 2.3 Intermediate data points of a selection task trajectory.

Movement Variability (MV). Movement variability (MV) represents the standard deviation of the distances between all data points $(x_i,\ y_i)$ of the selection trajectory and the task axis (see Eq. 2.5).

$$MV = \sqrt{\frac{\sum(y_i - \overline{y})^2}{n-1}} \tag{2.5}$$

Movement Error (ME). The movement error (ME) represents the mean absolute distance from all data points $(x_i,\ y_i)$ and the task axis (see Eq. 2.6).

$$ME = \frac{\sum(|y_i|)}{n} \tag{2.6}$$

Movement Offset (MO). The movement offset (MO) represents the mean distances between all data points (x_i, y_i) and the task axis. The difference between movement error and movement offset is that the former considers the absolute distance, and the later considers the coordinate distance (i.e., distance can have negative values) from the task axis (see Eq. 2.7).

$$MO = \overline{y} \tag{2.7}$$

Analyzing cursor trajectories from four different indirect input devices, namely, mouse, trackball, joystick, and touchpad, this study found strong negative relationships between these new measures and selection performance throughput, for all four devices. These relationships underlined that higher deviation from the task axis (that is indicated by the increased values in these new trajectory analysis measures) relates to lower performance throughput. Very strong positive inter-correlations among the trajectory measures were also observed. Among all trajectory measures, target re-entry (TRE) and movement offset (MO) were the strongest contributors for the lower performance throughput. Any measures that were strongly correlated to target re-entry and movement offset (e.g., orthogonal direction change for target re-entry, and movement variability and movement error for movement offset) had indirect influence on low performance throughput.

This study also elucidated performance differences across the abovementioned indirect input devices that previously could not be identified by measuring the selection time, error rate and performance throughput from Fitts's model. MacKenzie et al. (2001) did not reject Fitts's model as a mean of target selection performance analysis, rather stressed on using these new trajectory analysis measures as additional probes to better understand the reasons behind having target selection difficulties. More precisely, while Fitts's model detects the presence of selection difficulties from higher selection time, error rate, and lower performance throughput, the selection trajectory analysis measures can identify the potential causes for having such higher selection time, higher error rate, and lower selection performance throughput.

2.3 Effect of Aging on Target Selection Performance

Aging significantly affects motor, cognitive, and sensory capabilities relevant to interaction with computers and handheld devices. Motor changes include reduced range of wrist-motion (Chaparro et al., 2000), reduced muscle mass (Ketcham & Stelmach, 2004), and an increased noise-to-force ratio (Walker et al., 1997; Welford, 1981) that may lead to loss of fine motor control. In addition, age-related cognitive declines can result in slower information processing (Bashore et al., 1989; Salthouse, 1988; Welford, 1988) and slower reaction time (Ketcham & Stelmach, 2004; Walker et al., 1997). Aging can also cause sensory declines that may hinder efficient hand-eye coordination and visual feedback processing (Schaie, 2004; Schieber, 2003).

Prior studies have well documented the interaction difficulties encountered by older adults with indirect input devices, especially for the mouse. Research has shown that older adults have difficulty applying the correct amount of force on the mouse, leading to increased selection errors (Keates & Trewin, 2005; Ketcham & Stelmach, 2004; Walker et al., 1997; Welford, 1981). Error rates disproportionately increase as target widths decrease for older adults (Keates & Trewin, 2005). Loss of motor functionality has also been shown to hinder the ability to control the mouse, which can result in losing track of the cursor, difficulty positioning the cursor within the target bounds—often resulting in lower precision and higher endpoint selection variability (Chaparro et al., 1999; Keates & Trewin, 2005; Ketcham & Stelmach, 2004; Paradise et al., 2005; Riviere & Thakor, 1996; Smith et al., 1999; Walker et al., 1997). Older adults have also been found to encounter difficulties with more complex interaction tasks such as double clicking (Smith et al., 1999), clicking and dragging (Chaparro et al., 1999), and steering (Findlater et al., 2013). The combination of slower reaction time and loss of fine motor control can increase target selection time (Keates & Trewin, 2005; Smith et al., 1999; Walker et al., 1997; Welford, 1988). Task completion time disproportionately increases with age as the complexity of the task increases (Walker et al., 1997). The tendency among older adults to adopt a more conservative and error-averse target selection strategy results in more time spent on target verification prior to selection (Keates & Trewin, 2005; Salthouse, 1988; Smith et al., 1999; Walker et al., 1997; Welford et al., 1969). Emphasis on accuracy over speed also influences the movement profiles of older adults, which have lower peak velocities (Keates & Trewin, 2005; Ketcham & Stelmach, 2004), longer deceleration phases (Ketcham & Stelmach, 2004), and consist of smaller submovements punctuated with small verification pauses in place of the primary ballistic movement typical of younger adults (Keates & Trewin, 2005; Keates et al., 2005; Ketcham & Stelmach, 2004; Smith et al., 1999). Older adults also tend to initiate more corrective submovements than younger adults following a selection error (Keates & Trewin, 2005; Walker et al., 1997). Use of indirect input devices has also been found to cause fatigue and pain in the shoulder, neck, and wrist (Keates & Trewin, 2005; Paradise et al., 2005).

Despite not being as well-explored as indirect input devices, studies on age-related interaction difficulties with direct input devices (both pen and touch) have reached similar conclusions, with older adults demonstrating slower selection times (Findlater et al., 2013; Gao & Sun, 2015; Hourcade & Berkel, 2007; Ketcham et al., 2002; Moffatt & McGrenere, 2007; Rogers et al., 2005; Sultana & Moffatt, 2013) and higher error rates (Gao & Sun, 2015; Hourcade & Berkel, 2007; Moffatt & McGrenere, 2007; Sultana & Moffatt, 2013). Older adults have also been found to be more likely to encounter difficulties with complex tasks such as dragging (Findlater et al., 2013), steering (Findlater et al., 2013), and sliding (Rogers et al., 2005) with touch input. Target width has been shown to significantly influence error rates for pen input with aging – leading to disproportionately higher error rates with smaller targets (Hourcade & Berkel, 2007; Moffatt & McGrenere, 2007). Movement profiles of older adults with pen input are also consistent with that of mouse input having a combination of smaller submovements rather than a primary ballistic movement (Ketcham et al., 2002; Yan, 2000). Direct input devices are thought to have better support for hand-eye coordination than indirect input devices, which may explain the findings that direct input can reduce the performance gap (in terms of speed and accuracy) between older and younger adults (Atsuo & Iwase, 2002; Charness et al., 2004; Findlater et al., 2013; Murata & Iwase, 2005; Rogers et al., 2005; Schneider et al., 2008; Taveira & Choi, 2009).

2.4 Measures to Detect Age-related Performance Differences

As aging can influence significant performance differences between older and younger adults with both direct and indirect input devices, some prior studies dedicated their focus on understanding such performance differences. Some of these studies applied measures, such as number, types, and prevalence of selection errors, and others analyzed input device selection trajectories, across age groups and input devices.

2.4.1 Error Analysis across Age Groups

Prior works on selection error analysis for both mouse and pen interaction have shown a wider range of selection errors in older adults, compared to younger adults. Keates and Trewin (2005) demonstrated that with a mouse, older adults encountered two main categories of selection errors: (1) Miss errors, which is where the mouse button is both clicked and released (while aiming for a target) outside the target bounds. (2) Slip errors, which is where the mouse button is initially clicked for selection inside the target boundary, but is released outside the target area. As successful selection is typically defined by the location of the mouse cursor at the moment of the release of the mouse button, both slips and misses result in errors. This study showed that older adults encountered higher error rates than younger adults for both miss and slip errors. However, the proportions of miss errors were significantly higher than the slip errors with older adults. Keates and Trewin (2005) further sub-categorized the miss errors as follows:

Near Miss Errors. Mouse button clicks within 50% of the target radius away from the target boundary.

Not-so-near Miss Errors. Mouse button clicks between 50% and 100% of the target radius away from the target boundary.

Accidental Clicks Mouse clicks greater than 200% of the target radius away from the target boundary, possibly unintentional click.

Among these sub-categories, the near miss errors were the most common one among older adults with mouse input.

Moffatt and McGrenere (2007) extended Keates and Trewin's work (2005) to categorize age-related selection errors with pen input. They defined miss errors as when a pen is both landed and lifted up outside the target boundary, and slip errors as when a pen is landed inside the target boundary but is lifted up outside the target area. In contrast to the mouse interaction study (Keates & Trewin, 2005), this study concluded that slip errors are more predominant than miss errors with pen interaction in both age groups. Ninety percent of all selection errors encountered by older adults were either slip errors or near miss errors. Furthermore, with other sub-categories of miss errors, each contributed no more than 5% of selection errors. Slip errors were also found to increase with age, while miss errors remained similar across different age groups.

2.4.2 Trajectory Analysis across Age Groups

Although MacKenzie et al. (2001) studied selection trajectories of younger individuals with no motor impairment, they forecasted the applicability of these measures to understand accessibility requirements of different user populations, motor abilities, and input devices. Hwang et al. (2005) extended the work of MacKenzie et al. (2001) to address the performance differences in mouse interaction between individuals with and without motor impairments. This study introduced the following new trajectory analysis measures: number, percentage, duration, and location of pauses taken during a trial, target verification time, number of submovements, distribution of submovement end points, counter-productive submovements, cursor velocity, and distribution of submovement peak speed, in addition to applying a subset of the trajectory analysis measures from MacKenzie et al. (2001). This study reported clear distinctions on selection performance between groups. Individuals with motor impairments had frequent long pauses, long verification times, more target re-entries, and higher deviation from the target axis.

Trajectory analysis measures introduced by both MacKenzie et al. (2001) and Hwang et al. (2005) were further applied to explore age-related performance differences with pen input. Ketcham et al. (2002) studied the differences in the trajectory submovement structures, and the velocity profiles between older and younger adults. This study reported that, in tasks with higher index of difficulties, older adults generated a smaller initial submovement, followed by a number of corrective submovements with lower peak and mean speed. Sultana and Moffatt (2013) generated age-specific error prediction models, applying a subset of the trajectory analysis measures from prior works (Hwang et al., 2005; MacKenzie et al., 2001). These models achieved more than 90% accuracy rates on predicting errors in both older and younger adults. The study identified higher counts of pauses, movement direction changes, orthogonal direction changes, and task axis crossing as the most significant predictors for selection errors in older adults. While the main goal of this work was to generate error prediction models, these findings highlighted the viability of applying trajectory analysis measures to understand age-related selection difficulties.

2.5 Summary

The literature on target selection performance analysis reported significant performance differences between older and younger adults, across input devices and forms of interaction. Prior works on error analysis between age groups demonstrated that older adults encounter higher number and broader range of selection errors. These works also highlighted that differences exist in dominating error types, when the input device is different. Such difference in the dominating error types between mouse and pen input devices is particularly important because these results indicate that input devices may also influence the type of selection errors. However, because of the absence of any such studies with touch interaction from older adults, it is not clear if the nature of interaction (i.e., direct vs. indirect) is the reason for such differences in the proportion of miss and slip errors, or if it is the input device (regardless direct or indirect) that influences the type of errors. To answer these questions, we present a study in Chapter 3 that investigates age-related selection errors with touch input.

The body of literature on trajectory analysis studies confirmed that differences in selection trajectories exist between older and younger adults. Older adults have higher deviation from the task axis, have lower speed, and generate smaller corrective submovements such that they affect their overall selection performance with pen input. Similar conclusions were drawn about the performance of individuals with motor impairment for mouse input. However, missing from this literature is an account of how selection trajectory analysis could be applied on touch interaction to shed light on age-related selection difficulties. To fill this gap, we introduce three-dimensional trajectory analysis measures for touch interaction in Chapter 4. In Chapter 5, we present a study where we apply these measures to gather more insight on age-related performance differences with touch input.

Chapter 3

Selection Error Analysis

3.1 Introduction and Motivation

In Chapter 2, we demonstrated that prior works have reported various forms of age-related target selection difficulties, e.g., longer selection time and higher error rates with touch input (Findlater et al., 2013; Gao & Sun, 2015; Rogers et al., 2005). In-depth analyses of target selection errors for mouse (Keates & Trewin, 2005) and pen (Moffatt & McGrenere, 2007) interaction have documented two main categories of selection errors: (1) missing and (2) slipping. For mouse and pen interaction, both slips and misses were observed in older adults, but their relative proportions differed, with misses forming the dominant selection error type for mouse input, and slips for pen input. This difference suggests that input device may influence the kinds of target selection errors encountered by older adults. As similar studies have not been conducted for touch input, the most dominant age-related selection error type for touch input is not yet known. The study presented in this chapter addresses this research gap in the literature by extending the prior error analysis studies for touch input[1]. This chapter answers the first research question (*RQ1*) of this thesis:

> *RQ1.1. What types of selection errors are encountered by older adults with touch input?*
>
> *RQ1.2. Among all types of selection errors encountered by older adults, which one is the most predominant error?*

We conducted a controlled laboratory study with 20 older adults and 16 younger adults to answer *RQ1*. In this study, participants were asked to complete a two-dimensional Fitts's task-like target selection task (Fitts, 1954; Ren & Moriya, 2000) on a touchscreen smartphone. We measured the overall selection task performance (i.e., selection time, error rates, number of corrective attempts, selection endpoint variability, and finger pressure), and the types of selection errors that are encountered by older and younger adults. Younger adults were included as a comparison group to examine the influence of aging on performance. To understand the effect of aging on selecting very small targets, we chose smartphones as our touchscreen device that generally have smaller screens (around 150 mm diagonally), and very small targets (the smallest selectable items are about 5 mm).

Consistent with previous studies (Hourcade & Berkel, 2007; Keates & Trewin, 2005; Moffatt & McGrenere, 2007; Smith et al., 1999), we found that, relative to younger adults,

[1]Earlier versions of this chapter appeared as: Sultana and Moffatt (2017, 2019).

older adults required more selection time, encountered higher error rates, required a larger number of selection attempts to correct an error, demonstrated higher endpoint selection variability, put more pressure on the screen for selection, and accompanied with a broader range of selection errors. However, in terms of the types of selection errors encountered, notable differences emerged. In contrast to the findings of Moffatt and McGrenere (2007) for pen input, we found that for touch input, miss errors were more prevalent. Furthermore, we found that both slip and miss errors increased with age for touch input, whereas in Moffatt and McGrenere (2007), this relationship was only found for slip errors. These differences are notable given that both touch and pen input are direct forms of interaction and suggest that input method is an important factor influencing age-related target selection difficulty in nuanced ways that go beyond simple categorical groupings such as direct versus indirect input. They also highlight a potential tradeoff between pen and touch: while one explanation for the lower miss errors with pen input is that it offers a more precise selection point, touch input may result in fewer slip errors due to the increased friction provided by the finger.

3.2 Method and Materials

In this error analysis study, participants completed a finger calibration task (Bi et al., 2013)[2], and a two-dimensional Fitts's task-like target selection task (Fitts, 1954; Ren & Moriya,

[2] In the finger calibration task, participants were asked to select a 4.88 mm target that appeared at the centre of the screen. Finger calibration data was collected from three blocks, each containing 48 trials. This task was included in the hopes that it would provide additional insight into individual differences in selection endpoint variability, which we could then use to improve the index of difficulty (ID)-movement time (MT) fit for Fitts's model (Bi et al., 2013). However, it did not provide us with any additional insight, and thus, we do not report on them further.

2000) on a touchscreen smartphone in a controlled laboratory experiment. We recorded the selection time, error rates, number of corrective attempts to recover from an error, selection endpoint variability, finger pressure, and the types of selection errors encountered by older and younger adults, while varying target size, distance, and location. We also asked the participants to complete a number of standard neuro-psychological tests. Older adults' performance was compared to a younger adult control group.

3.2.1 Participants

We recruited 20 older adults (14 female and 6 male, aged 67–81, mean: 73.3, SD: 4.89) and 16 younger adults (12 female and 4 male, aged 22–35, mean: 28.9, SD: 3.73). All confirmed via self-report that they were right-handed, with no motor impairments to their right hands, and as having normal or corrected-to-normal vision, as per the inclusion criteria detailed in the call for participation.

All participants reported holding at least a high-school diploma (older adults) or a bachelor's degree (younger adults). Older adults reported using touchscreen devices for an average of 3.78 hours per week (SD: 4.66) and desk or laptop computers for an average of 17 hours per week (SD: 16.32). Younger adults reported spending an average of 19.46 hours per week on touchscreen devices (SD: 11.35) and 46.66 hours per week on desk or laptop computers (SD: 12.29). Four older adults reported no prior touchscreen experience, but basic to expert knowledge of desk or laptop computers. The remaining older adults rated their knowledge of touchscreen devices as basic to moderate and all younger adults rated their knowledge as moderate to expert.

We applied standardized tests to assess participants' sensory-perceptual and motor skills. Across the tests, we did not find any in-group differences, nor any outliers. The Digit Symbol Substitute Test (DSST) (Strauss et al., 2006) measures perceptual speed. As expected, older adult participants had lower scores, indicating lower perceptual speed: out of total 84 points, mean DSST score for older and younger adults were 54.2 (SD: 14.85) and 72.5 (SD: 16.30), respectively. The Letter Set Test (LST) (Strauss et al., 2006) was used to confirm fluid intelligence. Although the older group did score lower on this test than the younger group (as expected) the difference was not as large as we anticipated with both age groups performing poorly (older adults: mean = 12.71, SD = 6.18; younger adults: mean = 17.31, SD = 4.67, out of 30). Our informal observations suggest that older adults took a more conservative approach, preferring not to answer if in doubt. However, younger adults seemed to prioritize speed over accuracy, even though wrong answers were penalized in scoring the LST. Prior study on risk-taking behaviour across age groups reported that when possible losses were emphasized, older adults were more risk averse and younger adults showed more risk seeking behaviour (Mikels & Reed, 2009). Such age-related differences may have offset some of the expected differences in fluid intelligence that was reflected in our LST results. We additionally confirmed the ability to follow English instructions with the first 15 words of North American Adult Reading Test (NAART) (Strauss et al., 2006). All participants demonstrated high NAART score (older adults: mean = 13.9, SD = 1.29; younger adults: mean = 11.69, SD = 3.36, out of 15), indicating that both age groups had sufficient familiarity with the English language to correctly follow the experiment's instructions.

3.2.2 Apparatus

We used a Motorola Nexus 6 smartphone running the Android Lollipop 5.0.1 operating system for this study. The screen resolution of the device was 1440 $\times$ 2560 pixels and the screen size was 74.19 $\times$ 131.89 mm, resulting in 1 mm = 19.41 pixels (PPI = 493). The experiment was carried out in portrait orientation of the device, with the auto-rotate to landscape feature disabled. The experimental software was developed with Android Studio plugins for the Eclipse development environment.

3.2.3 Task

Participants completed a two dimensional Fitts's task-like selection task (see Figure 3.1), following a similar procedure to prior work (Ren & Moriya, 2000). At the beginning of each trial, a 7 mm wide circular start button appeared at the center of the screen. Upon successful selection of the start button, a red circular target appeared on the screen at one of the two predefined target amplitudes (20 mm and 30 mm), three predefined target widths (4.88 mm, 7.22 mm, and 9.22 mm), and eight predefined movement angles (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°; counter-clockwise) from the center of the start button. Target widths were chosen based on the widths used in Bi et al. (2013). However, we did not include the smallest size (2.88 mm) that was introduced to replicate ribbons in the one-dimensional Fitts's task. Our pilot testing demonstrated that 2.88 mm circular targets were too small for touchscreen interaction, even for the younger adults with no motor impairments. We added a larger 9.22 mm width, which is roughly the size of an icon of an Android phone. The combination of target amplitude (distance), width (size), and angular direction was determined randomly for each trial such that each unique combination appeared exactly once per block of 48 trials.

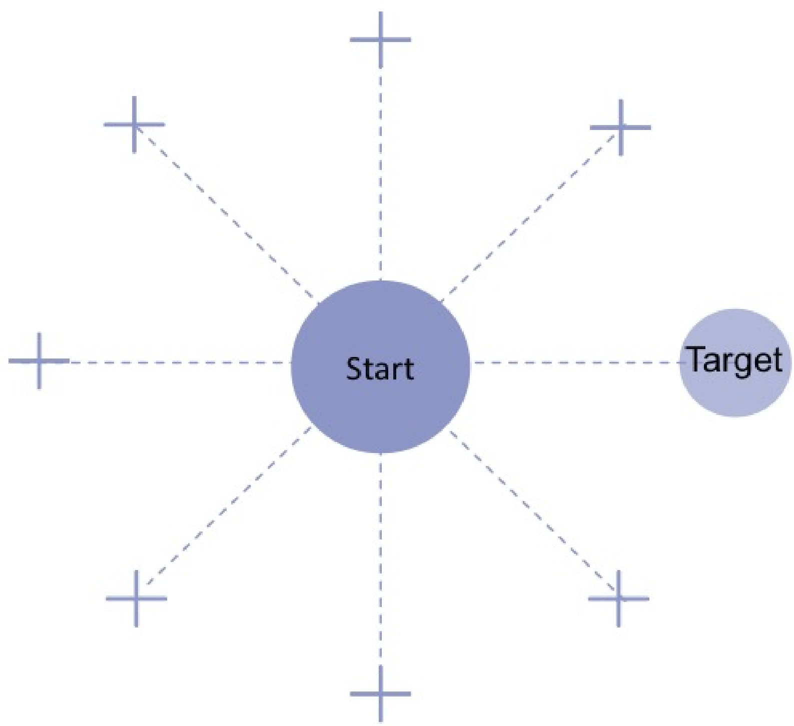


Figure 3.1 Two dimensional Fitts's task-like selection task showing 8 possible target locations (angles) relative to the Start button at the center of the screen. The circle labeled Target shows a sample target at the 0° angle. Angles are measured in counter-clock direction.

Participants were seated on a chair with no hand support, and were instructed to hold the device with their left hand and select targets with their right index finger as quickly and as accurately as possible. If they missed a target, they continued with the trial until the target was selected successfully. We asked for the corrective attempts until successfully acquiring the target for ecological validity and to enable us to estimate the cost of errors in terms of time and effort for recovery. Knowing the error recovery cost is important in understanding target selection, because a high error recovery cost can lead to frustration and further poor selection performance.

Before participants started the experiment, they were asked to complete a practice block consisting of six trials. Target amplitudes, widths, angles in the practice block were drawn from the same set as the actual task. A particular combination of amplitude × width × angle appeared only once, in a random order. Participants moved to the experiment task once they were comfortable with the practice trials. None of them required more than one block of practice trials (i.e., six trials). The two-dimensional selection task was carried out in four blocks, each containing 48 trials. Short breaks were given between the blocks as needed. All breaks were one minute or less. Participants were allowed to ask questions prior to and between trials. A timer was displayed at the top of the screen that showed the elapsed time of the current trial to give feedback on the movement time. The number of correct selections over the number of completed trials in the current block was displayed at the bottom of the screen to give feedback on the error rate. At the end of each block, the mean movement time and the number of correct selections for that block were displayed.

3.2.4 Measures

We recorded the following measures from all participants across both age groups:

Movement Time (ms). Movement time, measured in milliseconds (ms), was defined as the elapsed time from when the participant's finger lifted up off of the start button to the first lift up event following selection of the start button, regardless of whether or not this touch event successfully selected the target.

Error Rate (%). Errors were defined as trials in which more than one attempt was needed to successfully select the target. Error rate was thus the percentage of erroneous trials relative to all trials under consideration (e.g., all trials for an individual participant or at a particular target width or amplitude).

Finger Pressure. The Android pressure sensing API reports pressure on a scale from 0 to 1, where 0 is no pressure and 1 is the maximum pressure the device can measure. The Android device we used in this experiment, measures finger pressure from the finger surface that is in contact with the touchscreen, where more finger surface in contact means more pressure is applied on the screen. This measure is useful for comparing relative pressure differences as we report here, but cannot be converted into a real-world measure of force[3].

Selection Error Type (slips, misses). Based on the works of Keates and Trewin (2005), and Moffatt and McGrenere (2007) for mouse and pen interaction, respectively, we focused primarily on two sources of selection errors: slips, and misses. We also subcategorized the miss errors according to these prior works. Moreover, considering the higher proportion of slips relative to misses in older adults, with pen input that is also a form of direct interaction

[3]Documentation on the Android pressure-sensing API can be found in: https://developer.android.com/reference/android/view/MotionEvent

(Moffatt & McGrenere, 2007), we further subcategorized slip errors based on the distance slipped beyond the target bounds. Table 3.1 defines each of the error categories used in our analyses, comparing them to those reported in previous work.

3.2.5 Design

We used a 2 (age groups) × 4 (blocks) × 3 (target widths) × 2 (movement amplitudes) × 8 (movement angles) mixed design with all factors except for age as within-subjects factors. Each block consisted of 48 trials containing each unique combination of width × amplitude × angle exactly once, presented in a random order. Across the entire experiment, each participant completed 192 trials, resulting in a total of 3,840 trials from 20 older participants and 3,072 trials from 16 younger participants. We excluded trials with a movement time of more than three standard deviations away from the age group's mean movement time, as prior work (Findlater & McGrenere, 2010) has suggested. We thus removed 44 trials from the older adult group and 31 trials from the younger adult group, resulting in 3,796 and 3,041 trials for each group, respectively.

3.2.6 Procedure

Findlater et al. (2013) allocated older adults more time than younger adults to complete the same experiment, anticipating that they may require additional time to understand and follow the instructions. Following this prior study, we designed our experiment with the expectation that older adults would be able to complete the study session within 90

Table 3.1 Comparison of error categories. Each of the error categories used in this study, comparing them to those reported in previous work.

Definition	Keates and Trewin (2005)	Moffatt and McGrenere (2007)	Current Study
Input (i.e., mouse, pen, or finger) lands inside the target bounds, but lifts:			
At a distance less than 50% of the target radius away from the target boundary	Slip Error	Slip Error	Narrow Slip Error
Between 50% and 100% of the target radius away from the target boundary	Slip Error	Slip Error	Moderate Slip Error
Between 100% and 200% of the target radius away from the target boundary	Slip Error	Slip Error	Large Slip Error
At a distance greater than 200% of the target radius away from the target	Slip Error	Slip Error	Very Large Slip Error
Input (i.e., mouse, pen, or finger) lands outside the target bounds, and lifts:			
At a distance less than 50% of the target radius away from the target boundary	Near Miss Error	Near Miss Error	Near Miss Error
Between 50% and 100% of the target radius away from the target boundary	Not So Near Miss Error	Not So Near Miss Error	Not So Near Miss Error
Between 100% and 200% of the target radius away from the target boundary	[Not Reported]	Other Error	Other Error
At a distance greater than 200% of the target radius away from the target	Accidental Click	Accidental Tap	Accidental Tap

minutes, and younger adults within 60 minutes. All participants were allowed to take as much time as they needed, but all participants finished within the target time for their age group. Remuneration was based on the expected study session length. Older and younger participants received an honorarium of $15 and $10, respectively.

Each study session started with a brief introduction to the study along with a review of the consent process. Participants then completed a background questionnaire covering demographic data and computer experience. Next, participants completed a finger calibration task, followed by the Digit Symbol Substitute Test (DSST). They then completed the two-dimensional Fitts's task-like selection task, while the researcher conducting the session took observational notes on their target selection behavior. After the selection task, participants completed a questionnaire about their overall experience. They were then asked to read the first 15 words from the North American Adult Reading Test (NAART), as a rough indicator of their familiarity with the English language. They finished the session with the Letter Set Test (LST), followed by a short debrief and wrap-up session. The background questionnaire and the post-experiment questionnaire are included in Appendix A. All procedures were reviewed and approved by our institution's Research Ethics Board prior to commencement of the study. A copy of the Ethics Approval Certificate is included in Appendix E.

3.2.7 Analysis

We present the study results in terms of descriptive and inferential statistics. We applied repeated measure ANOVAs (2 age groups $\times$ 2 amplitudes $\times$ 3 widths $\times$ 8 angles, as defined in Section 3.2.5) to evaluate the main and interaction effects of our primary performance measures (i.e., movement time, error rates, finger pressure, and types of selection errors). All pairwise comparisons in the repeated measure ANOVAs were corrected with a Bonferroni correction. We also conducted Mauchly's test to identify sphericity violations, and corrected such violations with Greenhouse-Geisser corrections; where degrees of freedom (*df*) are non-integer, a correction has been applied. Along with statistical significance, we report partial eta-squared (η_p^2), a measure of effect size.

3.3 Results

In this section, we present our study results to answer *RQ1.1* and *RQ1.2*. We examine the overall performance effects of movement time and error rate, comparing our results to prior findings on aging and touch interaction in Section 3.3.1. We also present the overall selection performance in terms of number of corrective attempts to recover from an error, finger endpoint distribution, and finger pressure, across age groups. We dedicate the bulk of our attention to an analysis of age-related touch selection errors (*RQ1.1* and *RQ1.2*) in Section 3.3.2. Throughout the presentation of the results, we focus on our primary factors of interest and other significant main and interaction effects. Tables providing the full statistical results of all analyses are included in Appendix B. In presenting our results, we focus on comparisons of group means. We do not present individual participant data as no outliers were found in the data; i.e., no individual participant data were three standard deviations away from the group mean for any of the performance measures reported. A sub-group analysis comparing the 65–74 years old (n = 10) to those 75 and over (n = 10) did not reveal any differences.

3.3.1 Overall Performance

Movement Time

Consistent with previous findings on pen input (Moffatt & McGrenere, 2007), older adults were slower than younger adults and more variable in their performance (see Figure 3.2). Main effects were significant for all factors (age: $F_{1,33} = 19.01$, $p < .0005$, $\eta_p^2 = .37$, see Figure 3.2; width: $F_{1.17,38.59} = 37.46$, $p < .00001$, $\eta_p^2 = .53$, see Figure 3.3; amplitude: $F_{1,33} = 119.40$, $p < .00001$, $\eta_p^2 = .78$, see Figure 3.4; and angle: $F_{4.73,156.07} = 17.13$, $p < .00001$, $\eta_p^2 = .34$, see Figure 3.5). Pairwise comparisons confirmed that consistent with Fitts's law (Fitts, 1954), movement time increased as width decreased ($p < .00001$ for all pairs; Figure 3.3), and as amplitude increased ($p < .00001$ for all pairs; Figure 3.4).

Targets located in the lower-right corner (315°) were significantly slower to select than those in all other locations (all $p < .00001$) and targets in the upper-left corner (135°) were significantly slower to select than those in the lower-left corner (225°, $p < .05$). In addition, targets in the upper-right corner (45°) were the fastest to select, and significantly faster than those in the upper-left quadrant (90°: $p < .05$, 135°: $p < .001$, 180°: $p < .0005$), as shown in Figure 3.5. These findings are consistent with prior work on angular movement and pen input (Hancock & Booth, 2004), and reflect the effects of human physiology for

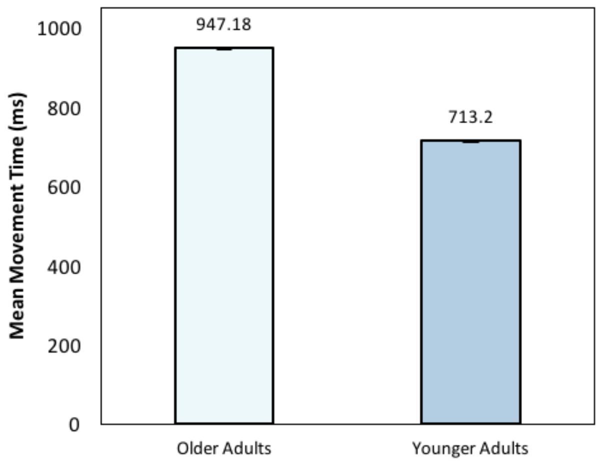


Figure 3.2 Mean movement times by age group (Older adults, $n = 20$; Younger adults, $n = 16$). Error bars show the standard errors.

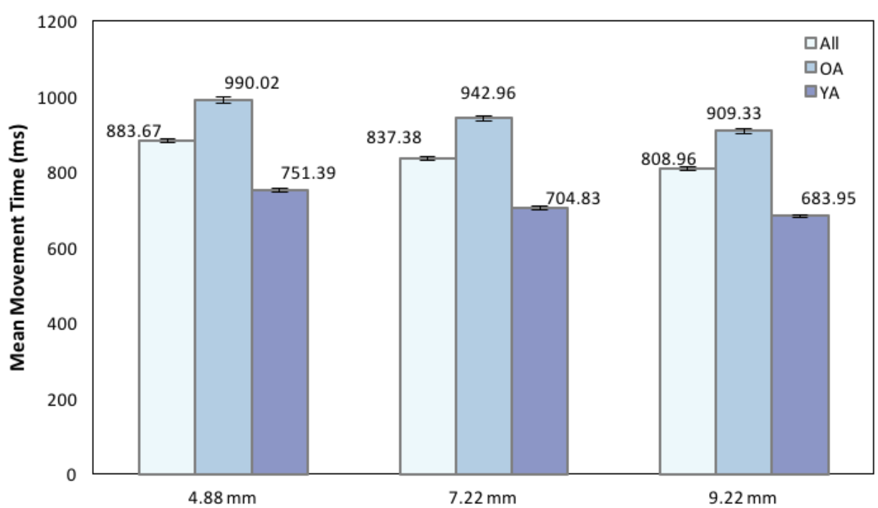


Figure 3.3 Mean movement times by target width ($N = 36$; OA = older adults, $n = 20$; YA = younger adults, $n = 16$). Error bars show the standard errors.

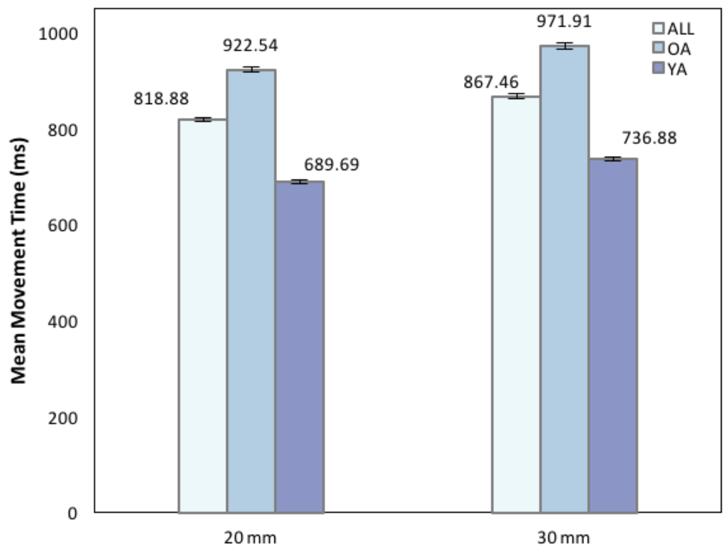


Figure 3.4 Mean movement times by target amplitude ($N = 36$; OA = older adults, $n = 20$; YA = younger adults, $n = 16$). Error bars show the standard errors.

right-handed individuals (i.e., radial movements to the upper-right are fastest) as well as right hand occlusion (i.e., targets to the lower-right are most likely to be occluded).

There was a significant interaction between width × amplitude ($F_{2,66} = 3.14$, $p = .05$, $\eta_p^2 = .09$). Pairwise comparison confirmed significant differences in movement time for all width-amplitude pairs (all $p < .00001$), but the impact of amplitude on movement time was somewhat less pronounced at larger target widths. No other interaction effects were significant, and in particular, there were no interaction effects with age, suggesting that older adults were not disproportionately slowed by decreasing target size, increasing movement amplitude, or by the particular angle of approach.

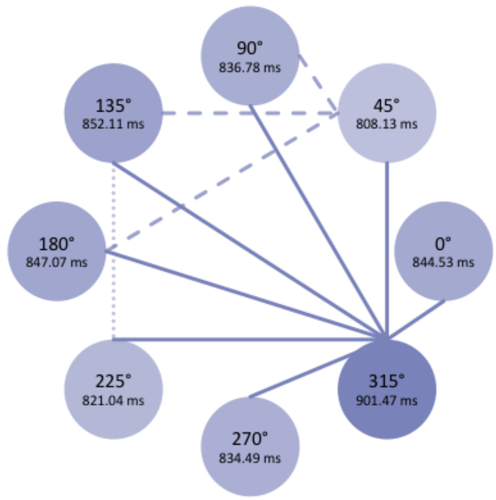


Figure 3.5 Mean movement times by target angle (N = 36; OA = older adults, n = 20; YA = younger adults, n = 16). Darker shades indicate longer movement times and connecting lines indicate significant pairwise differences. The pairwise differences with targets located at 315°, 45° and 135° angles are represented with solid, dashed and dotted lines, respectively.

Error Rates

In contrast to prior work on age-related differences in touch interaction (Findlater et al., 2013), we observed significantly higher error rates for older adults relative to younger adults ($F_{1,33} = 42.23$, $p < .0001$, $\eta_p^2 = .56$, see Figure 3.6). This difference is likely due to the different apparatus and different target widths used in the two studies. Our study was conducted on a 6.26 inches × 3.27 inches (diagonally 6 inches) smartphone, and Findlater et al. (2013) conducted their study on a 9.50 inches × 7.31 inches (diagonally 9.7 inches) tablet. Moreover, our largest target width (9.22 mm) was the smallest target width used by Findlater et al. (2013). Indeed, target width had a significant effect on error rate ($F_{1.35,44.68} = 153.60$, $p < .0001$, $\eta_p^2 = .82$, see Figure 3.7), and there was also a significant age × width interaction ($F_{1.35,44.68} = 27.68$, $p < .0001$, $\eta_p^2 = .46$, see Figure 3.8). Pairwise comparisons confirmed that error rates significantly increased as target width decreased (all $p < .0001$). While this pattern was true for both older and younger adults, error rates disproportionately increased for older adults at smaller target sizes, as shown in Figure 3.8 and reflected by the significant age $\times$ width interaction. Pairwise comparisons on this interaction effect confirmed that older adults had significantly higher error rates than younger adults for all target widths (for 4.88 mm: $p < .0001$; for 7.22 mm: $p < .00005$; for 9.22 mm: $p < .0005$). No other significant main or interaction effects were observed.

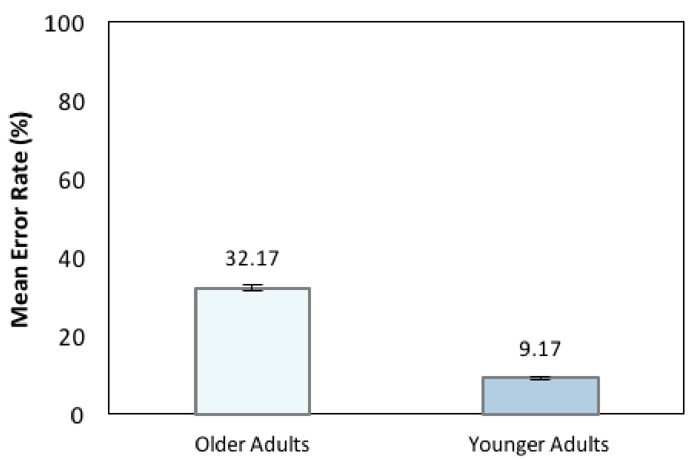


Figure 3.6 Mean error rate by age group, across all participants ($N = 36$) and by age group (older adults = OA, $n = 20$; younger adults = YA, $n = 16$). Error bars show the standard errors.

Corrective Attempts. To better understand the impact of age-related differences in error rates, we additionally considered the number of corrective attempts required to successfully select a target. Recall, that errors were defined as trials requiring more than one selection attempts; thus, an error free trial requires exactly one attempt, while an error trial requires two or more attempts (i.e., one initial attempt and one or more corrective

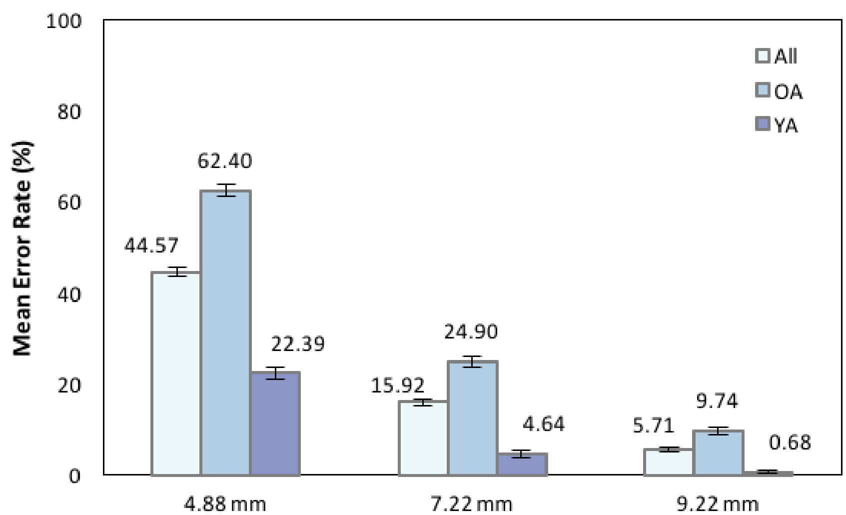


Figure 3.7 Mean error rate by target width, across all participants ($N = 36$) and by age group (older adults = OA, $n = 20$; younger adults = YA, $n = 16$). Error bars show the standard errors.

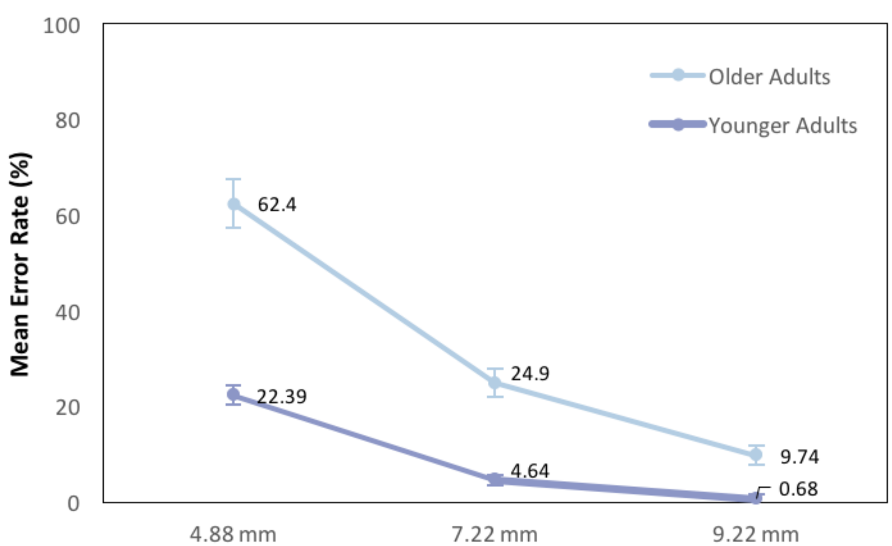


Figure 3.8 The interaction effect of age × width on error rate, for older adults ($n = 20$), and younger adults ($n = 16$). Error bars show standard errors.

attempts). As shown in Figure 3.9 and Table 3.2, older adults required more corrective attempts (minimum: 1, maximum: 54, median: 2) than younger adults (minimum: 1, maximum: 12, median: 1). For both age groups, the majority of errors were addressed with a single corrective attempt (older adults: 41% of 1221 error trials, younger adults: 67% of 279 error trials). However, while younger adults corrected all errors within 12 corrective attempts, older adults required more than 12 corrective attempts in 89 trials, which is more than 7% of the error trials from that age group. All participants (both younger and older) encountered difficulties to correct selection errors for the smallest targets, compared to the medium and largest targets (see Figure 3.10 and Table 3.3). While, all errors with the largest targets were corrected with at most 5 corrective attempts (for all participants), 8 trials for the medium targets, and 233 trials for the smallest targets, needed more than 5 corrective attempts. Older adults' substantial difficulties with recovering from errors with both medium and smallest targets were reflected by the higher number of corrective attempts with the medium (minimum: 1, maximum: 16, median: 1) and the smallest (minimum: 1, maximum: 54, median: 3) targets (see Figure 3.11 and Table 3.3). In Figure 3.12, we see that younger adults had a higher number of corrective attempts with the small targets (minimum: 1, maximum: 12, median: 1, see Table 3.3).

Selection Endpoint Variability. As prior work has shown that older adults demonstrate higher selection endpoint variability relative to younger adults for mouse input (Keates & Trewin, 2005) and pen input (Moffatt & McGrenere, 2007), we additionally examined the end point variability of the both age groups, by plotting the finger lift-up coordinates

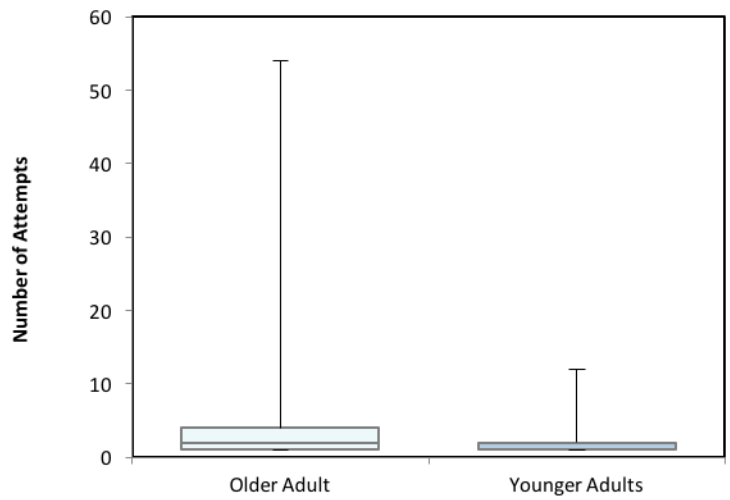


Figure 3.9 Boxplots showing the number of corrective attempts to recover from an error across age groups (Older Adults: $n = 20$; Younger Adults: $n = 16$).

Table 3.2 The maximum, median, and minimum number of corrective attempts to recover from an error across age groups (Older Adults: $n = 20$; Younger Adults: $n = 16$).

	Older Adults	**Younger Adults**
Maximum	54	12
Median	2	1
Minimum	1	1

Table 3.3 The maximum, median, and minimum number of corrective attempts to recover from an error for all participants ($N = 36$), older adults ($n = 20$), and younger adults ($n = 16$) across target widths.

	All Participants			**Older Adults**			**Younger Adults**		
Target Width (mm)	**4.88**	**7.22**	**9.22**	**4.88**	**7.22**	**9.22**	**4.88**	**7.22**	**9.22**
Maximum	54	16	5	54	16	5	12	3	3
Median	2	1	1	3	1	1	1	1	1
Minimum	1	1	1	1	1	1	1	1	1

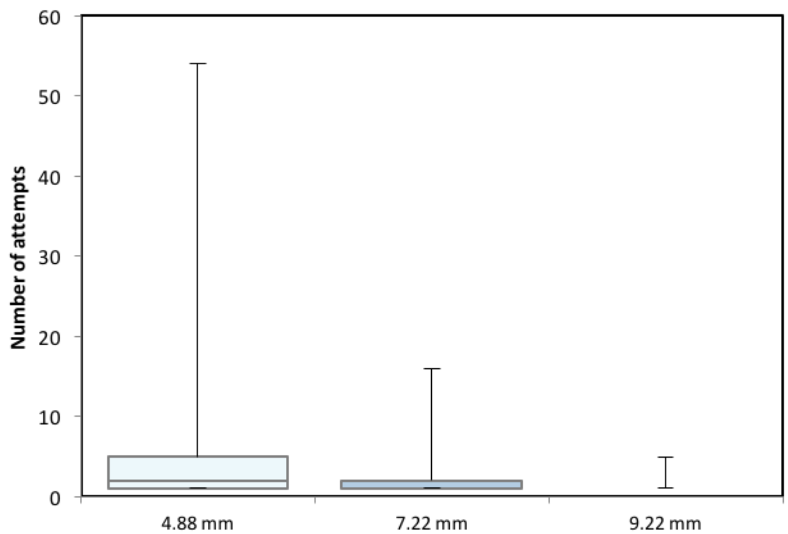


Figure 3.10 Boxplots showing the number of corrective attempts to recover from an error for all participants across target widths ($N = 36$).

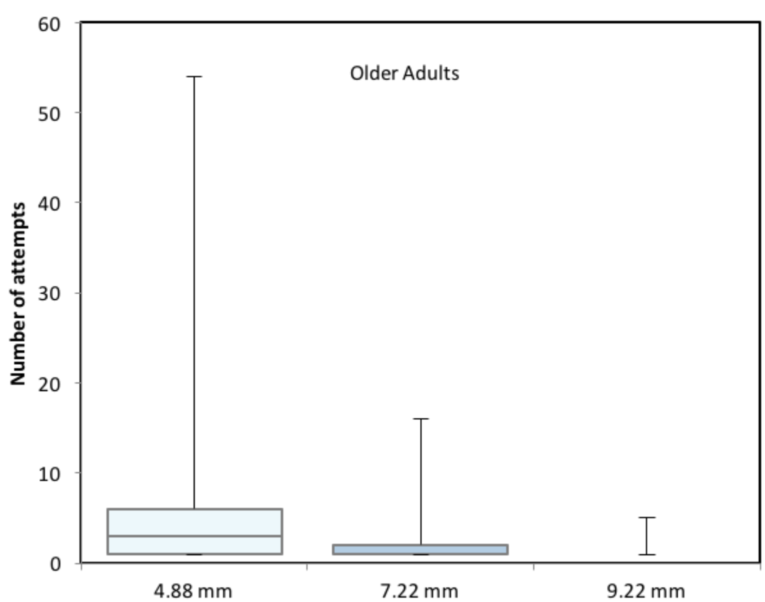


Figure 3.11 Boxplots showing the number of corrective attempts required for older adults ($n = 20$) across all target widths (4.88 mm, 7.22 mm, 9.22 mm) to recover from errors.

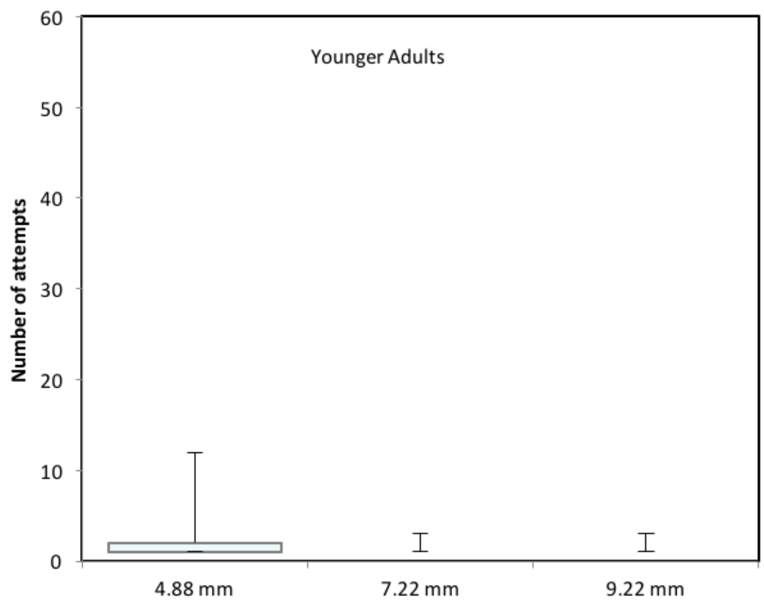


Figure 3.12 Boxplots showing the number of corrective attempts required for younger adults ($n = 16$) across all target widths (4.88 mm, 7.22 mm, 9.22 mm) to recover from errors.

from the first selection attempt of each trial. As shown in Figure 3.13, which plots the coordinates relative to the center of the target (regardless of where the target is actually located on the screen), the younger adults' selections were tightly clustered around the center of the target (mean distance from the target center = 1.92 mm, SD = 1.33), while the selections of the older adults were noticeably spread out, especially towards the lower-right of the targets (mean distance from the target center = 3.36 mm, SD = 4.40). The larger spread of selection endpoints of older adults reflects higher selection variability, relative to younger adults. To better understand the influence of target location, we also plotted this same endpoint data relative to the center of the start button (see Figure 3.14). Here we can see 16 distinct clusters, one for each combination of angle and amplitude. The higher spread of pixels in the lower-right quadrant of the left graph suggests a tendency for older adults to overshoot targets located to the lower right of the starting position, possibly in response to hand occlusion.

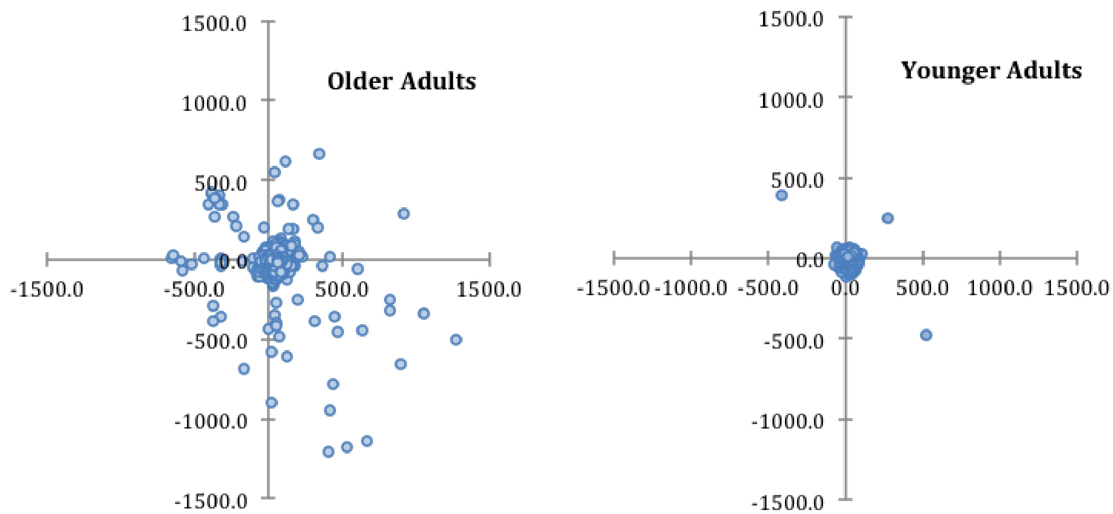


Figure 3.13 Selection endpoints relative to the center of the target, for older (left) and younger (right) adults measured in pixels (1 mm = 19.41 pixels).

Finger Pressure

Consistent with prior findings for pen interaction (Moffatt & McGrenere, 2010), older adults applied significantly more pressure during target selections than younger adults ($F_{1,33} = 8.18$, $p < .01$, $\eta_p^2 = .20$, see Figure 3.15).

The main effect of width on finger pressure was also found to be statistically significant ($F_{2,66} = 28.77$, $p < .00001$, $\eta_p^2 = .47$, see Figure 3.16). Finger pressure increased as target width increased. Pairwise comparison found significant differences between each pair of target widths (small-medium: $p < .005$, small-large: $p < .00001$, medium-large: $p < .0005$).

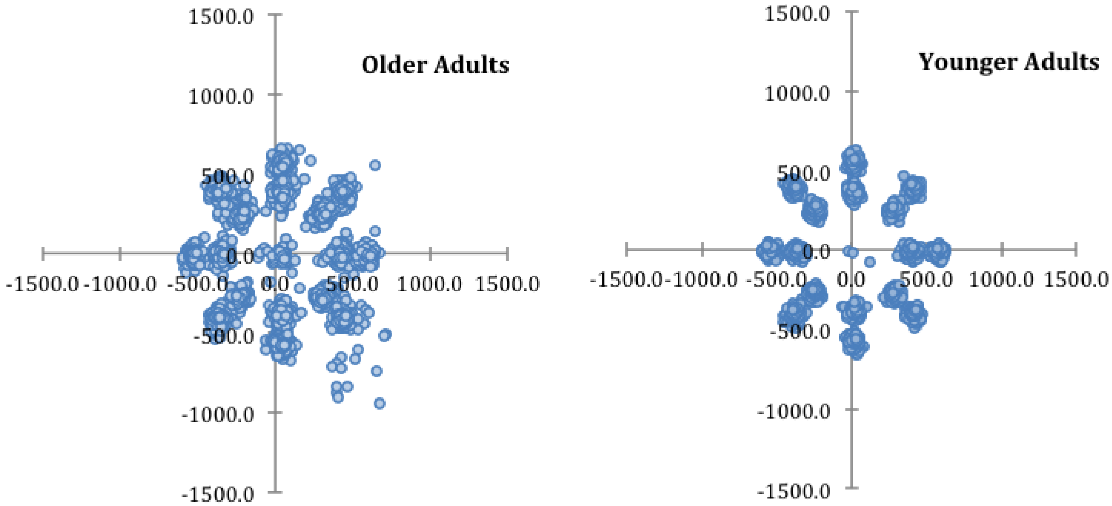


Figure 3.14 Selection endpoints relative to the center of the start button, for older (left) and younger (right) adults measured in pixels (1 mm = 19.41 pixels).

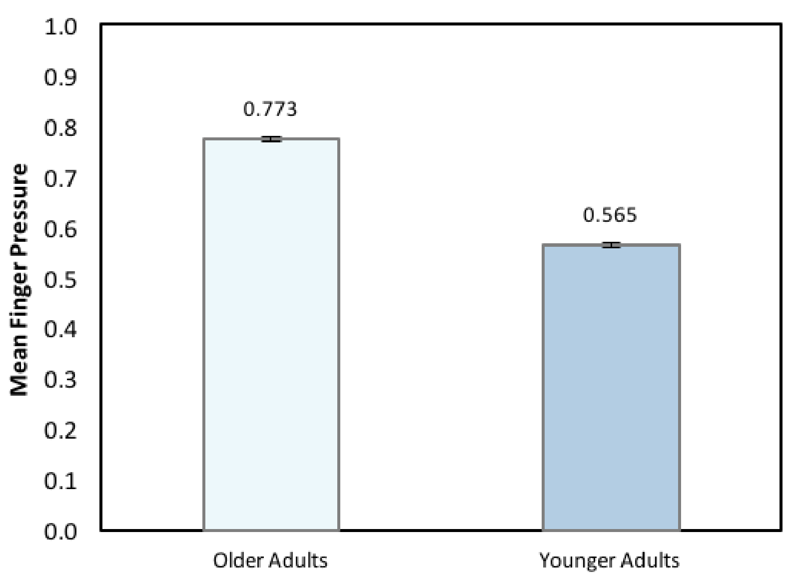


Figure 3.15 Mean finger pressure applied by age group (older adults, $n = 20$; younger adults, $n = 16$). Error bars show the standard errors.

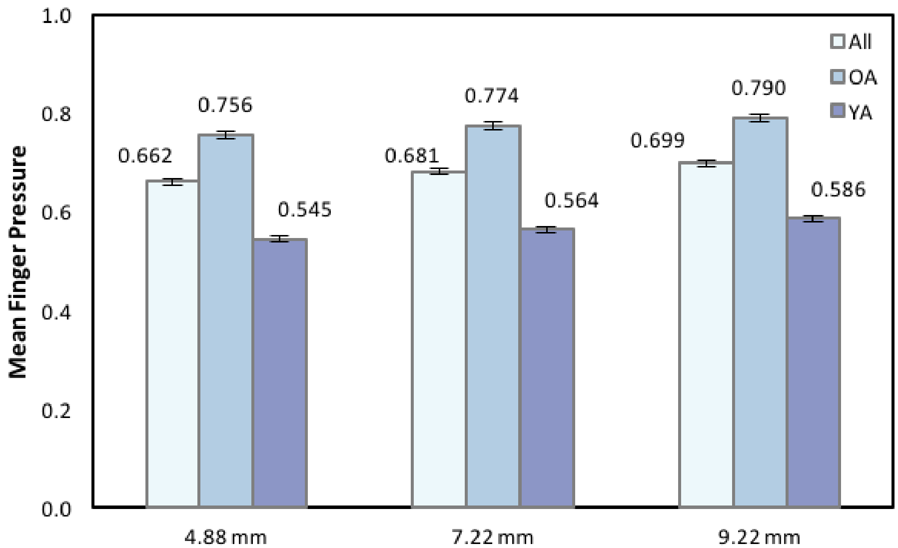


Figure 3.16 Mean finger pressure applied by target width across all participants (All: $N = 36$), older adults (OA: $n = 20$), and younger adults (YA: $n = 16$). Error bars show the standard errors.

Significant main effect of angle was observed on finger pressure (angle: $F_{3.42,231} = 10.67$, $p < .00001$, $\eta_p^2 = .24$, see Figure 3.17). Participants applied more pressure to select targets located at the upper-left quadrant than on the lower-right quadrant (Figure 3.17). The lowest mean pressure was applied on the lower-right corner (at 315° angle, mean = 0.642, SD = 0.268) and finger pressure increased gradually counter-clockwise until the target at the upper-left corner (at 135° angle, mean = 0.708, SD = 0.303). Then, finger pressure gradually decreased counter-clockwise until back again to the lower-right corner (315°). As seen in Figure 3.17, pairwise comparison also found significant differences in applied finger pressure between targets located at the lower-right, and the upper-left quadrants (at 0° angle, 45°: $p < 0.05$, 90°: $p < 0.05$, 135°: $p < 0.0005$, 180°: $p < 0.01$, 225°: $p < 0.005$; at 270°

angle, 135°: $p < 0.01$, 180°: $p < 0.01$, 225°: $p < 0.05$; at 315° angle, 45°: $p < 0.05$, 90°: $p < 0.05$, 135°: $p < 0.0001$, 180°: $p < 0.005$, 225°: $p < 0.00005$).

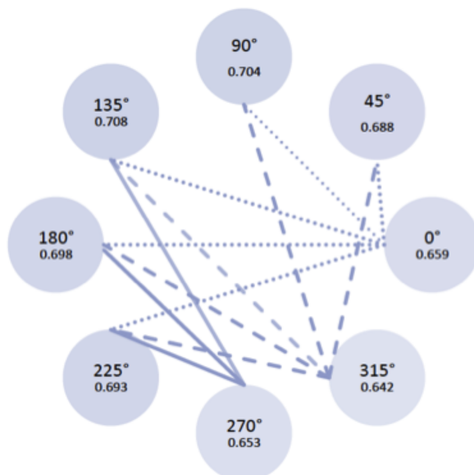


Figure 3.17 Mean finger pressure applied by movement angle, across all participants ($N = 36$). Darker shades indicate higher finger pressure applied and connecting lines indicate significant pairwise differences. The pairwise differences with targets located at 0°, 270° and 315° angles are represented with dotted, solid, and dashed lines, respectively.

No main effect of amplitude was observed. We also did not find any interaction effects of age with width, amplitude, or angle. However, our analysis found significant interaction effect of amplitude × angle on finger pressure ($F_{4.58,151.06} = 2.48$, $p < .05$, $\eta_p^2 = .07$).

As we noticed significant differences in finger pressure across age groups, target widths, and target angles, we anticipated that higher pressure (i.e., more finger surface area in contact with the screen) may have increased the error rates of older adults. However, when we further investigated the influence of finger pressure on error rates across age, target widths, amplitudes, and angles, no significant correlations were evident between finger pressure and error rates across these factors.

Subjective Analysis

In our post experiment questionnaire, we asked participants to reflect on their speed, error rate, difficulty level and preference of target width, amplitude and location. Responses generally aligned with the performance results presented in this sections. All older adults reported that the smallest targets were the slowest, most error-prone, and most difficult to select, and thus, were the least preferred. Younger adults also had similar comments about the smallest targets. Twelve out of sixteen describing them as the most time consuming, error-prone, difficult, and least preferred. However, there were some differences in the most preferred target size. All older adults (20/20) preferred the largest target size—reporting that it was the fastest, least error-prone, and least difficult to select, while 6/16 younger adults described the largest size as too big and preferred the medium targets.

Both older and younger adults faced difficulty with selecting the targets located at the lower-right quadrant and at the left side of the screen. Four older adults reported particular difficulty with the smallest target when it was located at the lower-right quadrant as the right hand blocks the view of the target; 3 noted difficulty with the horizontal-left (180°) and lower-left (225°) positions due to the longer travel distance. Two younger adults reported that the smallest targets at the left side of the screen were more difficult to select: one preferred targets on the vertical (top (90°) and bottom (270°) of the screen) positions, while the other preferred targets in the horizontal-right position (0°). Some (3/16) younger participants reported that smallest targets located diagonally (45°, 135°, 225°, and 315°) were the most difficult ones to select.

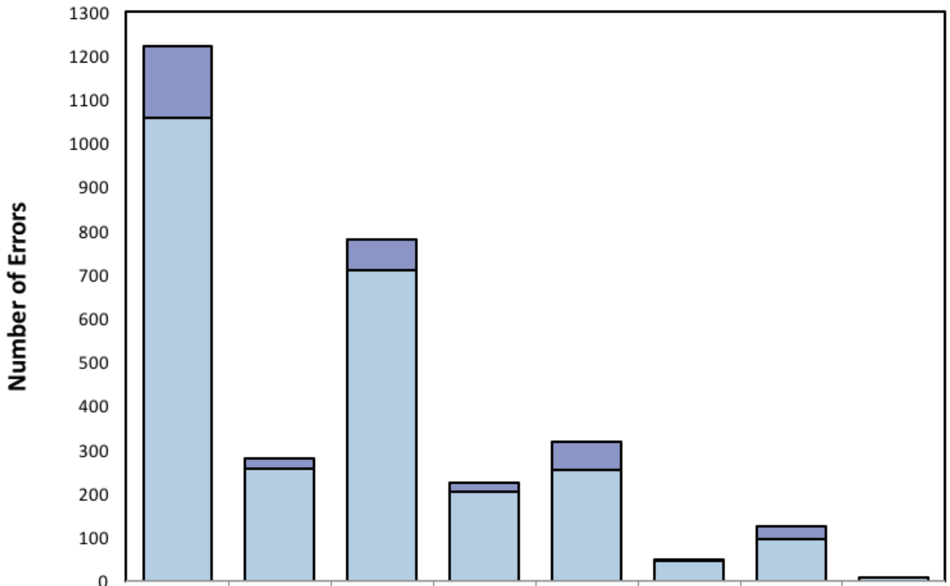
Finger size, position and pressure also had impact on selection difficulty in both age groups. Some participants from both age groups (older: 5/20, younger: 1/16) commented that their finger was bigger than the smallest targets, making it difficult to see whether they were within the target bounds. One older adult mentioned that placing the finger vertically on the target before the final selection reduced their error rate, and one noticed that putting less pressure on the screen helped reduce selection errors.

3.3.2 Distribution of Target Selection Errors

We now turn our attention to the different types of selection errors encountered. For both older and younger adults, miss errors dominated over slip errors, with older adults making over six times, and younger adults making over ten times as many miss errors than slip errors, respectively, as shown in Table 3.4. In Figure 3.18, we further provide the distribution of major error types across each target width. The stacked bars show that the general pattern holds across widths: at every width, misses outnumbered slips by at least a factor of four.

Table 3.4 Miss and slip error distributions for older and younger adults.

	Total Trials	**Miss Errors**			**Slip Errors**		
		Total	*Rate (%)*	*SD*	*Total*	*Rate (%)*	*SD*
Older Adults	3796	1058	27.87%	44.84	163	4.29%	20.27
Younger Adults	3041	255	8.39%	27.72	24	0.79%	8.85



	OA (1221)	YA (279)	OA (780)	YA (225)	OA (317)	YA (47)	OA (124)	YA (7)
	All Target Widths		4.88 mm		7.22 mm		9.22 mm	
Slip Error	163	24	70	21	65	3	28	0
Miss Error	1058	255	710	204	252	44	96	7

Figure 3.18 Distribution of slip and miss errors for all trials, and across each target width for older ($n = 20$) and younger ($n = 16$) adults.

Miss Errors

Older adults encountered over four times as many miss errors as younger adults (see Table 3.4), a difference that was statistically significant ($F_{1,33} = 36.27$, $p < .0001$, $\eta_p^2 = .52$). There was also a significant effect of target width on miss errors ($F_{1.27,41.96} = 141.36$, $p < .0001$, $\eta_p^2 = .81$, see Figure 3.18) with pairwise comparisons revealing that miss errors increased as width decreased (for all pairs: $p < .00001$). A significant age $\times$ width interaction effect ($F_{1.27,41.96} = 27.71$, $p < .00001$, $\eta_p^2 = .46$) shows that miss errors disproportionately increased for older adults relative to younger adults as width decreased (see Figure 3.19). Pairwise analysis confirmed that for all widths, older adults had significantly higher miss error rates than younger adults (small targets: $p < .00001$, medium targets: $p < .0001$, large targets: $p < .001$). Moreover, older adults had disproportionately higher miss error rates as target width decreased (all pairwise target widths: $p < .0001$). Younger adults had significantly higher miss error rates with the smallest target width ($p < .00005$ for the small-medium, and for the small-large width pairs), but no difference was observed between the medium and largest widths ($p = 0.49$). No other significant main or interaction effects were observed.

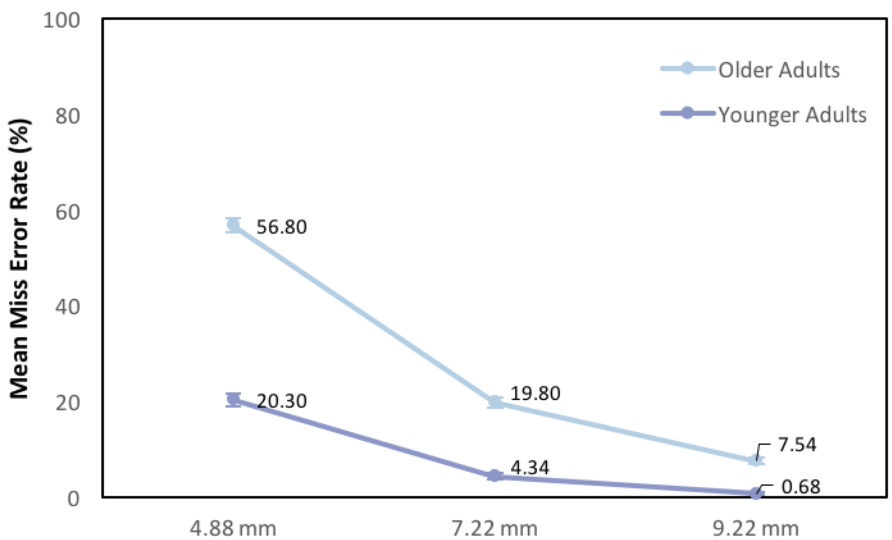
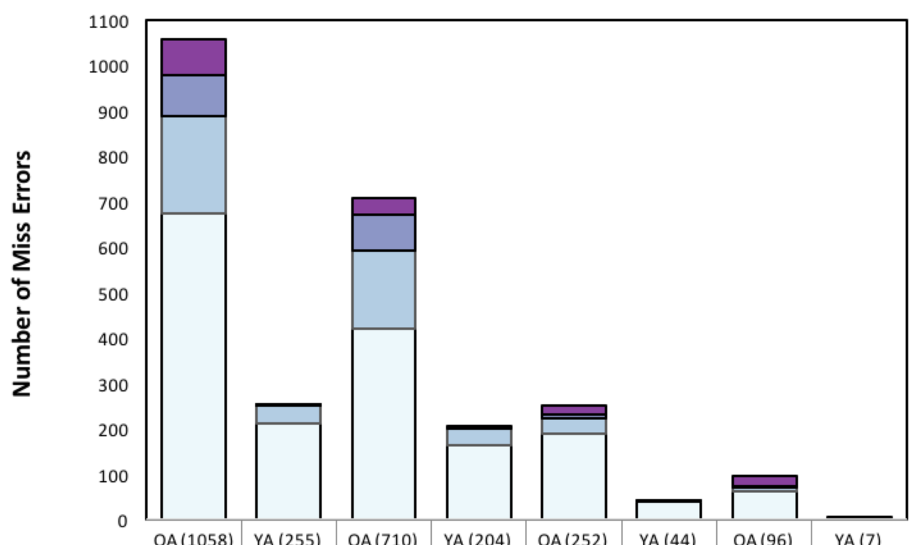


Figure 3.19 Mean miss error rates at each target width, for older ($n = 20$), and younger ($n = 16$) adults.

Similar to prior works on mouse and pen interaction (Keates & Trewin, 2005; Moffatt & McGrenere, 2007), the majority of miss errors were near miss errors, occurring within 50% distance of the target radius away from the target boundary (see Figure 3.20). Near miss errors accounted for 64% and 84% of miss errors for older adults (675/1058) and younger adults (213/255), respectively. Consistent with our overall findings for miss errors, the number of miss errors in each sub-category increased as target width decreased for both age groups. The distribution of miss errors in each sub-category across target widths mostly followed the overall pattern for miss errors (i.e., near miss > not-so-near miss > other > accidental taps, in terms of proportions). However, older adults were prone to accidental taps for all target widths, having more accidental taps than other errors (19 vs. 10) with medium targets, and more accidental taps than not-so-near miss errors (20 vs. 8) and other errors (20 vs. 4) with the large targets. To better illustrate the relationship between distance and miss errors, histograms with a bin size of 25% of the target radius are included for both age groups and across all target widths in Appendix B.



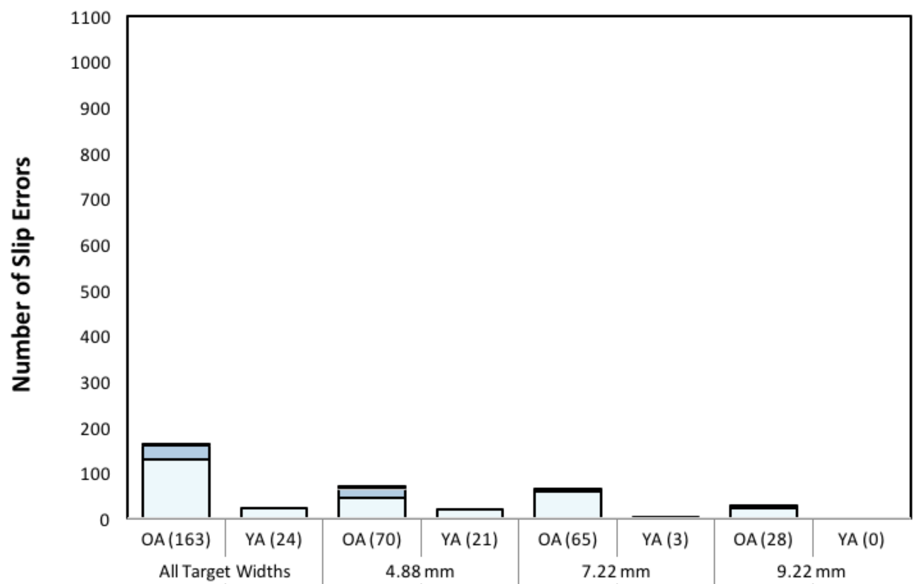
	All Target Widths		4.88 mm		7.22 mm		9.22 mm	
	OA (1058)	YA (255)	OA (710)	YA (204)	OA (252)	YA (44)	OA (96)	YA (7)
Accidental Tap	77	3	38	1	19	2	20	0
Other	92	1	78	1	10	0	4	0
Not-So-Near-Miss	214	38	172	36	34	2	8	0
Near Miss	675	213	422	166	189	40	64	7

Figure 3.20 Breakdown of miss errors by subcategory for older ($n = 20$) and younger ($n = 16$) adults. Across age groups and target widths, near miss errors mostly dominated over all other subcategories of miss errors.

Slip Errors

As with miss errors, older adults generated significantly more slip errors than younger adults ($F_{1,33} = 9.94$, $p < .005$, $\eta_p^2 = .23$), making over six times as many (see Table 3.4). There was also a significant effect of target width on slip errors ($F_{1.34,44.28} = 7.27$, $p = .0054$, $\eta_p^2 = .18$, see Figure 3.18), with pairwise comparisons revealing that slip errors were lower for the largest target width than for the medium ($p < .001$) and smallest ($p < .01$) widths, but no difference was found between the medium and the smallest widths ($p = .611$). Unlike the miss errors, the age $\times$ width interaction on slip errors was not significant ($p = .195$), potentially due to the much lower overall rate of slip errors than miss errors observed in our study.

Figure 3.21 shows the distribution of slip errors across the sub-categories. Narrow slip errors (i.e., those less than 50% of the target radius away from the target boundary) dominated, accounting for 80% (131/163) of slip errors for older adults and all (24/24) slip errors for younger adults. For older adults, the bulk of the remaining slip errors (18%, 29/163) were moderate (i.e., between 50% and 100% of the target radius away), with the remaining two categories only accounting for 1 and 2 slip errors each, respectively. The distribution of slip errors in each sub-category across target widths mostly followed the overall pattern, i.e., number of slip errors in each category decreased as width increased. There was only one exception, where there were somewhat more narrow slips on the medium sized target than the smallest (60 vs. 46). The proportions of errors in each sub-category (narrow >



	OA (163)	YA (24)	OA (70)	YA (21)	OA (65)	YA (3)	OA (28)	YA (0)
	All Target Widths		4.88 mm		7.22 mm		9.22 mm	
Very Large Slip	2	0	2	0	0	0	0	0
Large Slip	1	0	1	0	0	0	0	0
Moderate Slip	29	0	21	0	5	0	3	0
Narrow Slip	131	24	46	21	60	3	25	0

Figure 3.21 Breakdown of slip errors by subcategory for older ($n = 20$) and younger ($n = 16$) adults. For both age groups and for all target widths, narrow slip errors dominated over all other subcategories. Younger adults did not slip on the 9.22 mm targets.

moderate > large > very large) were also fairly consistent across target widths, except for the smallest targets, where there were more very large slip errors than large slip errors (2 vs. 1). More fine-grained histograms detailing slip error distances across age and target widths are included in Appendix B.

3.4 Discussion

Our findings both confirm the results of prior research on age-related target selection performance and broaden these results with a more detailed analysis of the kinds of selection errors older adults encounter during touch interaction. Our study found that older adults encounter both miss and slip errors during target selection with touch input (*RQ1.1*), among which miss errors are the most predominant errors (*RQ1.2*).

3.4.1 Movement Time Increases with Age and Decreases with Target Size

Consistent with prior work, older adults were significantly slower than their younger counterparts. Although we did not measure the number and the duration of pauses during a target selection task, we observed older adults pausing as they neared the target regions before finalizing their selection, which may have contributed to the longer selection times for older adults as has been observed for mouse (Keates & Trewin, 2005) and pen (Ketcham et al., 2002) interaction. Our movement times across target width and amplitude also aligned with previous work on mouse (Keates & Trewin, 2005) and pen (Moffatt & McGrenere, 2007) input in that both groups were slower with smaller and more distant targets. Like prior results on angular movement with pen input (Hancock & Booth, 2004), we also observed that selecting the upper-right targets were faster than selecting the lower-right targets. Participants (both younger and older) also had relatively quicker selection time with the vertical (top and bottom) targets, and slower selection time with the upper-left targets. We did not find any interaction effect between age and width, amplitude, or angle, meaning that older adults were not disproportionately slowed by any of these factors.

3.4.2 Smaller Targets Disproportionately Reduced Accuracy for Older Adults

With respect to accuracy, older adults made significantly more errors, and showed a greater selection endpoint variability than younger adults. These results are consistent with past findings for mouse (Keates & Trewin, 2005; Keates et al., 2005; Ketcham & Stelmach, 2004; Smith et al., 1999; Walker et al., 1997) and pen (Hourcade & Berkel, 2007; Ketcham et al., 2002; Moffatt & McGrenere, 2007) inputs, but differ from past findings for touch input, which found no relationship between age and errors (Findlater et al., 2013). A likely explanation for this departure—and one that is consistent with the significant interaction effect we observed between age and target width—is the different target sizes used in the two studies: our largest target width of 9.22 mm was the smallest target width used by Findlater et al. (2013). Note that our smallest targets (4.88 mm) were roughly the size of a menu icon on the Android phone used in our experiment, so the difficulty participants encountered reflects a real problem affecting individuals on a daily basis, and potentially hindering adoption. In addition to making more errors, older adults in our study required more corrective attempts to recover from them. While most targets were acquired with just one (no error) or two (one error and one corrective) attempts, over 15% of trials on the smallest target (4.88 mm) required 10 or more corrective attempts for the older adults. Such trials were frustrating for participants and reflect substantial difficulty acquiring small targets. All older adult participants reported in the post-experiment questionnaire that relative to the other target sizes, they encountered more errors and required more corrective attempts to select the smallest targets, which made such targets to be the most difficult ones to select. While troublesome from an accessibility standpoint, this result is not entirely unexpected: similar studies with younger non-impaired individuals have also observed high error rates for small targets with touch input (Bi et al., 2013; Cockburn et al., 2012; Sasangohar et al., 2009), and even though the smallest targets were less problematic for our younger adult participants, the majority (12/16) reported difficulty with them. Difficulties with small targets have been attributed to the "fat finger problem" in which the shape of the finger, its size relative to the target, and misconceptions about the exact location of the selection point reduce pointing precision and hinder target verification prior to selection (Holz & Baudisch, 2011; Vogel & Baudisch, 2007). Some of our participants made similar comments about their finger being larger than the smallest targets might have caused lower selection rate. Thus, our results may suggest a tipping point, with small targets representing a manageable inconvenience for younger adults but presenting a barrier to use for older adults.

3.4.3 Miss Errors are More Prevalent than Slip Errors

In terms of the types of selection errors encountered, older adults exhibited a broader range of selection errors than younger adults. While younger adults slipped rarely, older adults both slipped from and missed targets (though misses dominated over slips for them as well). This result is somewhat surprising. Although it aligns with the pattern previously observed for mouse input (Keates & Trewin, 2005), it differs from that observed for pen input (Moffatt & McGrenere, 2007), despite both pen and touch being forms of direct interaction. This difference may point to a tradeoff. As the tip of a pen is much smaller than a finger, pen input affords higher precision, potentially reducing misses; however, fingers offer higher friction against the screen than a hard-plastic pen tip, potentially reducing slips. Additionally, aging contributed to both miss and slip errors in our study for touch interaction, but was only observed to contribute to slip errors for pen input (Moffatt & McGrenere, 2007). We also observed a higher proportion of accidental taps for older adults, relative to prior studies on mouse (Keates & Trewin, 2005) and pen (Moffatt & McGrenere, 2007) input.

3.4.4 Affordance Matters

During our study sessions, we observed a number of difficulties encountered by older participants, including finding a suitable angle to position the finger on the target and determining which part of the finger needs to be in contact with the screen to register a touch. Participants explored a number of strategies to overcome these difficulties. Many tried adjusting their finger angle and rotation, while others tried to roll their fingers to select targets with the sides of their fingertips. Most promisingly, some adopted a strategy in which they intentionally landed outside the target bounds and then dragged their fingers into the target before lifting. This technique has been previously observed by Potter et al. (1988) and Moffatt et al. (2003), but relies on a solid understanding of how selection occurs. While some successfully adopted this approach in our study, we observed that others were unclear on when the selection registers. Some older participants expected that landing their fingers inside the target boundary should be sufficient to correctly select the target. In this study we analyzed finger lift-up data, where a touch is registered. Future studies might benefit from analyzing finger touch-down data to gain more insight on the initiation of a selection.

3.5 Design Implications and Recommendations

Considering to our study results, in which both miss and slip errors significantly decreased at our maximum target size of 9.22 mm, and the results of Findlater et al. (2013), in which no significant differences were found for accuracy across target sizes of 9.22 mm and larger – a starting guideline would be to ensure all targets are at least 9.22 mm wide. Although this is consistent with the standard icon sizes of 9 to 10 mm of the most popular smartphones, many selectable elements on current devices can be as small as 5 mm (roughly the size of our smallest target). Thus, it is likely not possible to simply make all selectable items as large as 9.22 mm, given the current constraints on screen real estate, especially in smartphones (Lee et al., 2009). At the very least doing so would require making accommodations elsewhere that could introduce other potential accessibility barriers for older adults (e.g., additional cognitive loads introduced by increased scrolling). This also suggests that there is a need for designing novel touch input selection techniques for older adults to improve the accessibility of such devices. A primary focus can be exploring alternative approaches to easily select smaller targets that can also address age-related selection difficulties. While no prior studies have specifically addressed the problem of older adults selecting small targets using touch input, inspiration can be taken from other existing accessible selection techniques that have been designed for other populations encountering similar selection difficulties, other input devices, or addressing specific selection difficulties similar to the difficulties that our study identified. The following subsections highlight some potential selection techniques from prior studies that we can draw inspiration for designing accessible touch selection techniques for older adults. It has to be noted that further studies on these techniques are required to assess their viability and effectiveness in reducing age-related performance differences with touch interaction, as they may introduce new accessibility challenges.

3.5.1 Selection Techniques Designed for Very Small Targets

Although this error analysis study focused on the selection difficulties encountered by older adults, we detected higher error rates (22.39%) with the 4.88 mm targets in younger adults. Some prior works also reported selection difficulties in younger adults with targets that are 5 mm or smaller that motivated designing a number of new selection techniques to address this challenge. *Offset cursor* (Potter et al., 1988) applied a finger-mouse strategy to drag the finger to the target to avoid missing targets that are slightly smaller than the finger, while *slide-touch* used a similar strategy, but with a pen to select very small (1.88 mm) targets (Ren & Moriya, 2000). We also observed some older adults applying a similar strategy to land their fingers outside the target boundary and then slide them inside the target boundary, before the final lift up, to reduce their error rates. Zooming-like techniques, for example, *cross-keys* (Albinsson & Zhai, 2003), *precision-handle* (Albinsson & Zhai, 2003), *rub-pointing* (Olwal & Feiner, 2003), and *control display manipulation* (Albinsson & Zhai, 2003; Benko et al., 2006) have shown promise for increasing pointing precision at the pixel level for younger adults. *Shifting* (Vogel & Baudisch, 2007) was found to be successful for selecting very small targets, especially those located at the edge of the screen and are difficult to select by zooming and offsetting techniques. Alternative approach include *back of the device interaction* (Baudisch & Chu, 2009), which makes use of the back of the screen for input, was successful with very small touchscreen devices (diagonally 63 mm, similar to the smartphone used in this study). Our selection endpoint analysis demonstrated that selection endpoints of older adults are usually leaned towards the lower-right corner of the actual target locations. Similar endpoint distribution was also observed in younger adults with smaller targets (Holz & Baudisch, 2010). Holz and Baudisch (2010) designed *finger print tracking*, which uses the finger print to better detect selection points, instead of using the precise finger-lift up location. These selection techniques can be examined for older adults when designing larger targets is not a feasible option.

3.5.2 Selection Techniques Designed to Reduce Miss Errors

Design implications for accessible interfaces can be effective if they address the most dominating selection errors encountered with that particular input device. Our study results demonstrated that major proportion of errors with touch input were miss errors in both older and younger adults. Moreover, miss error rates disproportionately increased in older adults as the target size got smaller. This means, for developing accessible touch interaction techniques for older adults, future research must emphasize on minimizing miss errors. Literature on error analysis studies demonstrated that miss errors are the most prevalent errors for mouse input, and techniques like *area cursor* (Worden et al., 1997), *target expansion* (McGuffin & Balakrishnan, 2002) and *bubble cursor* (Grossman & Balakrishnan, 2005a) were successful to reduce such errors. Extending these selection techniques for touch input can be a starting point to reduce miss errors in older adults, and thus, may improve their selection performance. These techniques require prior knowledge of the mouse cursor locations that may pose challenges to extend them for touch input, as commercial touchscreen devices natively do not track fingertip locations when the finger is not in-touch with the screen. Additional technologies, for example, motion sensors can be combined with touchscreen devices to provide fingertip locations during a selection. The most prominent reasons behind higher miss error rates are finger occlusion and hand tremor due to motor declines, especially, when the target is substantially smaller than the finger (Bi et al., 2013; Holz & Baudisch, 2010). Prior works on *mid-air pointing* (Cabreira & Hwang, 2018) and *silk-cursor* for 3-D pointing (Zhai et al., 1994) can be considered to address finger occlusion challenges with touch input. Another approach to address finger occlusion can be including haptic feedback inside the target boundaries such that users have clear indication when their finger does not land inside the target boundaries, and if so, they can slide their finger inside the target to avoid the potential miss errors.

3.6 Summary

In this chapter, we extended prior studies on error analysis with mouse and pen input to gain deeper understanding on age-related selection errors with touch input. Consistent with past findings (with mouse and pen input), older adults in our study required longer movement times, generated higher error rates, and encountered broader range of selection errors that needed more error corrective attempts for recovering, compared to younger adults. Study results also conformed to the selection endpoint variability and angular movement behavior as reported in previous studies with mouse and pen interaction. Our investigation on the range of selection errors concluded that miss errors are more prevalent than slip errors for touch interaction in both younger and older adults. These results, when compared to previous findings for pen interaction, indicate that even though both pen and finger are direct input selection devices, selection errors vary across these two mediums. Moreover, selection errors found in touch input shows more similarities with that of mouse input (i.e., both having misses as the dominating selection error), despite the former is a direct and the latter is an indirect form of interaction. Differences in the selection errors between pen and touch input suggest that accessible pen interaction techniques for touchscreen devices – that are designed for older adults – may not improve selection performance with touch input for the same population. Our findings suggest that more in-depth analysis is required to identify the reasons behind age-related selection difficulties with touch input. Analysis of finger movement properties in selection trajectories may provide valuable insight on selection difficulties that are encountered by older adults, as it was useful to understand selection difficulties with mouse (Hwang et al., 2005; Keates & Trewin, 2005; MacKenzie et al., 2001; Wobbrock & Gajos, 2008) and pen (Ketcham et al., 2002) input. In the next two chapters we will examine touch input trajectories to gather more knowledge about age-related selection difficulties. In Chapter 4, we will introduce a number of touch input trajectory analysis measures that can reflect on low performance throughput with touch input. In Chapter 5, we will present detailed analysis of performance differences across age groups that are observed in these touch input trajectory measures.

Chapter 4

Trajectory Analysis Measures for Touch Input

4.1 Introduction and Motivation

In the last chapter (Chapter 3), we demonstrated that aging can introduce a range of selection difficulties with touch input. The error analysis study presented in that chapter confirmed that older adults required significantly longer selection time, generated more errors, and encountered a broader range of selection errors, compared to younger adults. The performance difference across groups were more pronounced with smaller targets that were roughly the size of selectable menu items in touchscreen interfaces. These findings motivated us to further investigate selection difficulties with touch input, particularly, identifying selection behaviours that are closely associated with generating low performance throughput in older adults.

Prior studies on target selection performance evaluation have primarily focused on overall task performance, for example, speed, accuracy, and throughput (MacKenzie, 1992; Soukoreff & MacKenzie, 2004). A small body of work has suggested that analysis of the input device's cursor trajectory to the target can provide an additional lens on performance (MacKenzie et al., 2001). Such analysis can also help to distinguish performance differences between age groups (Keates & Trewin, 2005; Ketcham et al., 2002; Sultana & Moffatt, 2013) and motor abilities (Hwang et al., 2005; Wobbrock & Gajos, 2008) with mouse and pen input devices. Although these prior works suggest a promising avenue for understanding age-related performance differences with touch input, to date touch input trajectory analyses have not been explored.

One of the differences between mouse and touch input trajectories[1] is – the former produces two-dimensional trajectories, whereas the latter produces three-dimensional trajectories. Directly applying the mouse cursor trajectory measures from prior works on touch input may not fully capture the three-dimensional properties of finger trajectories. In this chapter, we lay the ground work to apply finger trajectory measures for distinguishing age-related performance differences with touch input (to be presented in Chapter 5). In this chapter, first, we developed a set of new three-dimensional finger trajectory analysis measures by extending two-dimensional measures from past works on mouse cursor trajectories (Hwang et al., 2005; Keates & Trewin, 2005; MacKenzie et al., 2001), along with three touch input

[1] From this point forward, we will refer to *touch input trajectory* as *finger trajectory*.

measures (Holz & Baudisch, 2011). Second, we examined the reliability of these new finger trajectory measures, as these measures have never been applied before on touch input. We identified selection difficulties through these trajectory measures that affected the performance throughput of the selection task. In particular, we answered the following research question (*RQ2*) of this thesis:

> *RQ2.1. What is the relationship between each of the three-dimensional finger trajectory analysis measures and performance throughput for touch input?*
>
> *RQ2.2 How do these finger trajectory analysis measures relate to each other?*

To answer these questions, we conducted a controlled laboratory study with 16 older and 16 younger adults. We custom-built a finger trajectory data collection tool by combining a touchscreen tablet and a motion-sensing device. Finger trajectory data were collected from a Fitts's task-like target selection task (Fitts, 1954; Ren & Moriya, 2000). We followed the same procedure from prior work on mouse trajectory analysis measures (MacKenzie et al., 2001) to answer *RQ2.1* and *RQ2.2*. We first conducted pairwise correlation analyses between each of the finger trajectory measures and performance throughput to understand their relationships. Strong and significant negative correlations were identified between throughput and a subset of the finger trajectory measures. These measures were associated with frequent long pauses, higher counts in finger direction changes, and longer travelled path along the selection trajectory. Our study results highlighted that higher values observed in these trajectory measures can indicate lower performance throughput in touch input. Our relationship analysis among the finger trajectory measures identified three clusters of measures. Trajectory measures within these clusters had strong and significant positive correlations and significantly strong interdependencies with each other.

4.2 Three-Dimensional Finger Trajectory Analysis Measures

The differences between the two-dimensional and three-dimensional trajectories of indirect and direct input devices impact the definition of the ideal performance of a selection task. In indirect interaction, the input device cursor entirely remains in the two-dimensional screen of the device, forcing the whole selection trajectory to take place within that two-dimensional device screen, as shown in Figure 4.1. Cursor movements exist relative to the two-dimensional coordinate space of the device's display (hereafter referred to as the *device plane*). Ideal performance is defined as the movement along the shortest Cartesian path from the user's starting position to the center of the target, known as the task axis (MacKenzie et al., 2001). An ideal task axis aligns with the x-axis (i.e., $y = 0$ for simplicity) of the corresponding movement vector. Cursor movement deviation is measured as the two-dimensional deviation from the ideal task axis (i.e., when $|y| > 0$).

In direct interaction, the input device (i.e., pen or fingertip) does not remain in touch with the two-dimensional device screen during the entire target selection task. Arguably, a major portion of the direct input trajectories takes place in the three-dimensional space (i.e., beyond the two-dimensional device screen), when the pen or finger is in the air, not

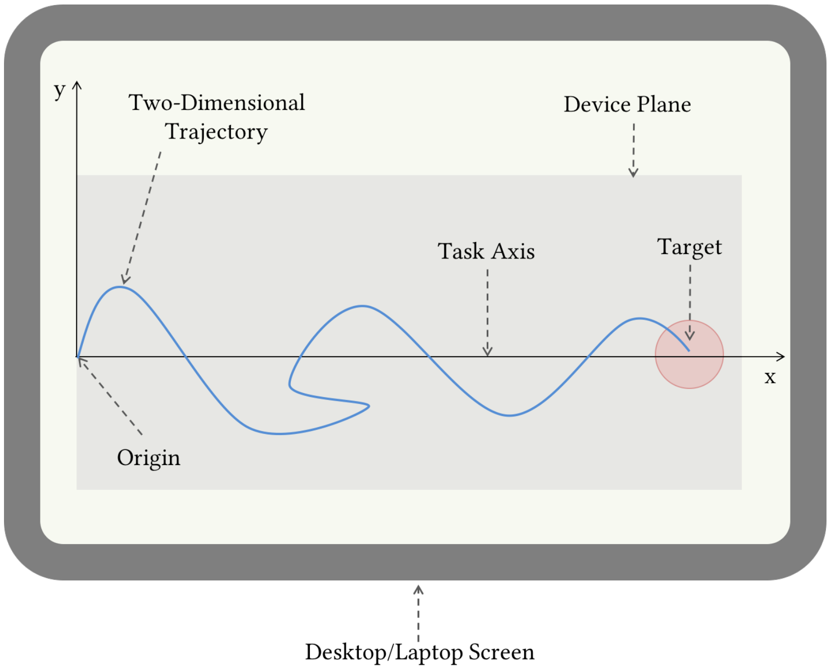


Figure 4.1 A two-dimensional indirect input trajectory. The x-y plane is the device plane. Task axis is the shortest two-dimensional distance between the starting position and the target center.

touching the device screen, as shown in Figure 4.2. The definition from ideal performance of indirect input devices becomes inapplicable for touch interaction, because the finger must lift off the screen or a drag, rather than a selection, will be initiated. Thus, we argue that ideal performance is better defined in three-dimensions as movement within a *task plane*, where this plane is defined as passing through the task axis (the shortest Cartesian path from the user's starting position to the center of the target, same as indirect interaction), orthogonally[2] intersecting with the device plane (see Figure 4.2). That is, if we assume the device plane is the x-y plane (i.e., $z = 0$), with the task axis running along the x-axis

[2]In a real life interaction, an individual can hold a touchscreen device at any angle, and can be in a seated, standing, or reclined position. That is why, we define the task plane to be orthogonal to the device plane, instead of being parallel to the horizontal plane.

$(y = 0, z = 0)$, then the ideal task plane is the x-z plane $(y = 0)$. As a starting point, we define the ideal performance as an arc within the x-z plane from the starting position to the target center. The height of this arc (i.e., the z-value) should be small (to minimize path distance to the target), but non-zero (to avoid initiating a drag), with the exact ideal height unknown at this time (see Figure 4.2). Similarly, movement deviations also need to be measured as three-dimensional deviation from the task plane, instead of the two-dimensional deviation from the task axis.

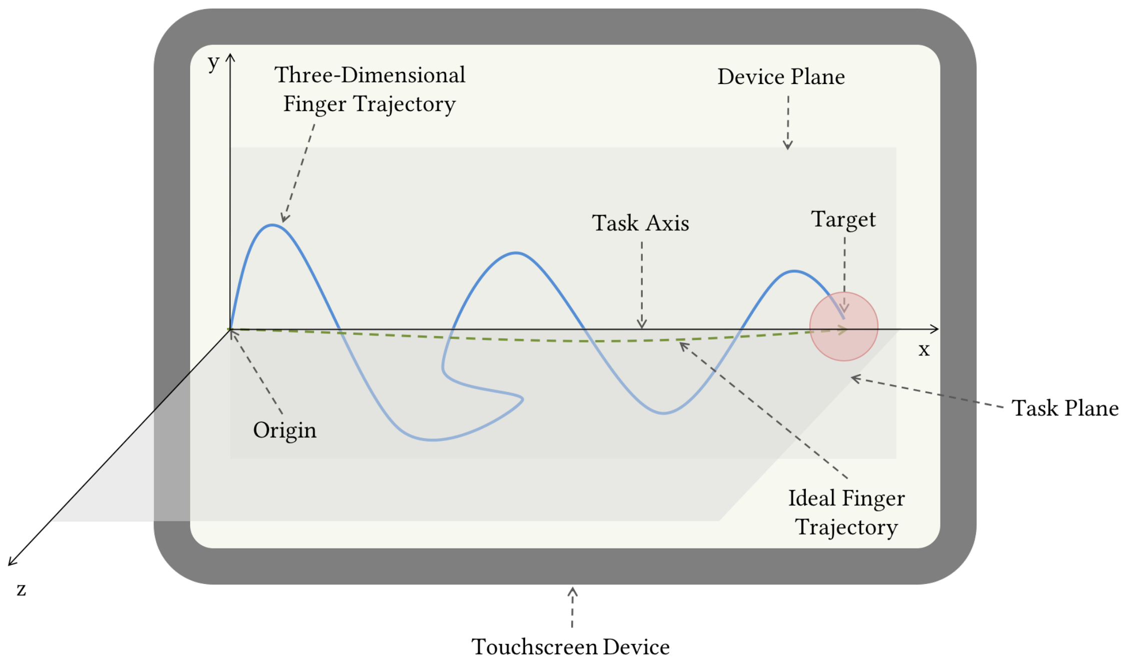


Figure 4.2 A three-dimensional finger trajectory. The x-y plane is the device plane and the x-z plane is the task plane. Task axis is the shortest three-dimensional distance between the starting position and the target center.

Because of the differences in the ideal performance between direct and indirect interaction, the existing two-dimensional performance analysis measures are not applicable for analyzing the three-dimensional touch input trajectories. Some may argue that prior works on pen interaction, which is a form of direct interaction, have applied the existing two-dimensional cursor trajectory analysis measures to explore age-related differences in selection performances (Ketcham et al., 2002; Sultana & Moffatt, 2013). Although pen trajectories are three-dimensional, the analyses conducted in these works were based on the two-dimensional cursor trajectories recorded from an inductive pen, and did not consider the three-dimensional movement of the pen itself. To gather a complete insight on touch (or direct) interaction, especially to capture the trajectory properties beyond the device plane, these existing two-dimensional trajectory measures should be extended to three-dimensional trajectory measures. Otherwise, finger trajectory analysis will be incomplete.

To develop an initial set of possible three-dimensional trajectory analysis measures, we collated and extended two-dimensional mouse cursor trajectory measures from MacKenzie et al. (2001). Moreover, we extended and included a subset of mouse cursor trajectory measures from Keates and Trewin (2005), and Hwang et al. (2005), as these measures were developed by design to understand the selection difficulties encountered by older adults, and individuals with motor impairment, respectively. We also included finger rotation measures from prior work that showed promising results to understand selection difficulties with touch input (Holz & Baudisch, 2011). All of these new three-dimensional measures are summarized in Table 4.1. Measures from MacKenzie et al. (2001) and Keates and Trewin (2005) are related to the path of movement and have been defined as various forms of deviation from the ideal performance. These prior measures required further elaboration to accommodate the three-dimensional movement path and deviation of finger trajectories, with the respect to the ideal task plane and the three-dimensional movement vector, relative to the task. To calculate these measures, we considered x-axis of the movement vector to be always aligned with the task axis, regardless the target location. On the other hand, the measures related to pausing and speed (Hwang et al., 2005), and finger rotations (Holz & Baudisch, 2011) are relatively straightforward and could be directly mapped from prior work. We describe the new three-dimensional trajectory measures in Section 4.2.1, followed by presenting the implications of these measures on understanding selection difficulties in Section 4.2.2.

4.2.1 Finger Trajectory Measure Definition

In this section, we define the three-dimensional finger trajectory measures. Details on data collection and calculation of these measures are included in Section 4.3.6.

Direction Changes Along All Axes (DC-X, DC-Y, DC-Z)

Using the above definition of ideal touch performance, we redefined and extended orthogonal and movement direction changes from MacKenzie et al. (2001) that count the parallel and orthogonal direction changes of the cursor, respectively. These measures were renamed as direction changes along the x-axis (DC-X), and direction changes along the y-axis (DC-Y), respectively. Another corresponding measure, direction changes along the z-axis (DC-Z), was introduced to account for the direction changes towards and away from the device plane (see Figure 4.3). All three measures are reported as the number of direction changes per trial.

Table 4.1 Three-dimensional finger trajectory measures with their definitions, origins, and units. All measures are relative to a single selection trial.

New Measures	Measures from Prior Works
Direction Changes	
Direction Change X-Axis (DC-X)	Orthogonal Direction Change (ODC) (MacKenzie et al., 2001)
Direction Change Y-Axis (DC-Y)	Movement Direction Change (MDC) (MacKenzie et al., 2001)
Direction Change Z-Axis (DC-Z)	New Measure
Task Plane Crossing (TPC)	Task Axis Crossing (TAC) (MacKenzie et al., 2001)
Movement Deviation	
Movement Offset (MO)	Movement Offset (MO) (MacKenzie et al., 2001)
Movement Error (ME)	Movement Error (ME) (MacKenzie et al., 2001)
Movement Variability (MV)	Movement Variability (MV) (MacKenzie et al., 2001)
Path Axis Ratio (PAR)	Path Axis Ratio (PAR) (Keates & Trewin, 2005)
Pause	
Pause Frequency (PF)	Number of Pauses (Hwang et al., 2005)
Pause Duration (PD)	Mean Pause Duration (Hwang et al., 2005)
Pause Location Distance (PLD)	Mean Pause Location Distance (Hwang et al., 2005)
Speed	
Peak Speed (SP)	Peak Speed (Hwang et al., 2005))
Mean Speed (SM)	New Measure
Rotation	
Mean Pitch (RP)	Mean Pitch (Holz & Baudisch, 2011)
Mean Yaw (RY)	Mean Yaw (Holz & Baudisch, 2011)
Mean Roll (RR)	Mean Roll (Holz & Baudisch, 2011)

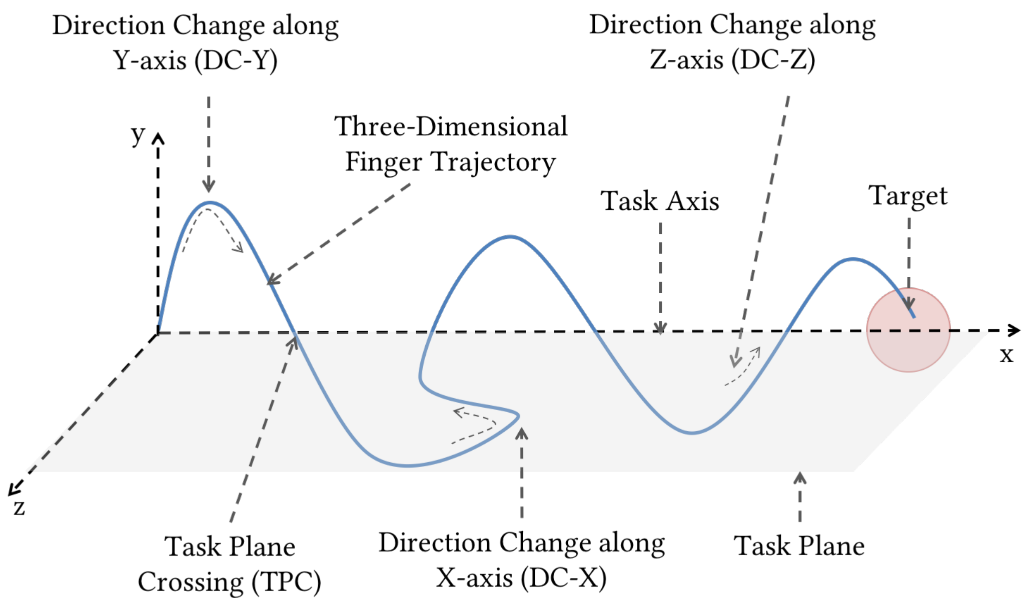


Figure 4.3 Direction changes along the x-, y-, and z-axis (DC-X, DC-Y, DC-Z), and task plane crossing (TPC) in a three-dimensional finger trajectory.

Task Plane Crossing (TPC)

The number of task axis crossings from MacKenzie et al. (2001) was adjusted to the number of task plane crossings (TPC). Task plane crossing (TPC) counts the number of times finger crosses anywhere in the task plane per trial (see Figure 4.3).

Movement Offset, Error, and Variability (MO, ME, MV)

The movement deviation measures: movement offset (MO), error (ME) and variability (MV) from MacKenzie et al. (2001) were likewise updated to correspond to the task plane. Movement offset (MO), error (ME) and variability (MV) represent the mean of the signed distances, mean of the absolute (not signed) distances, and standard deviation of the signed distances, between fingertip locations and the task plane, respectively. All of these measures are reported per trial and are presented in millimeters (mm).

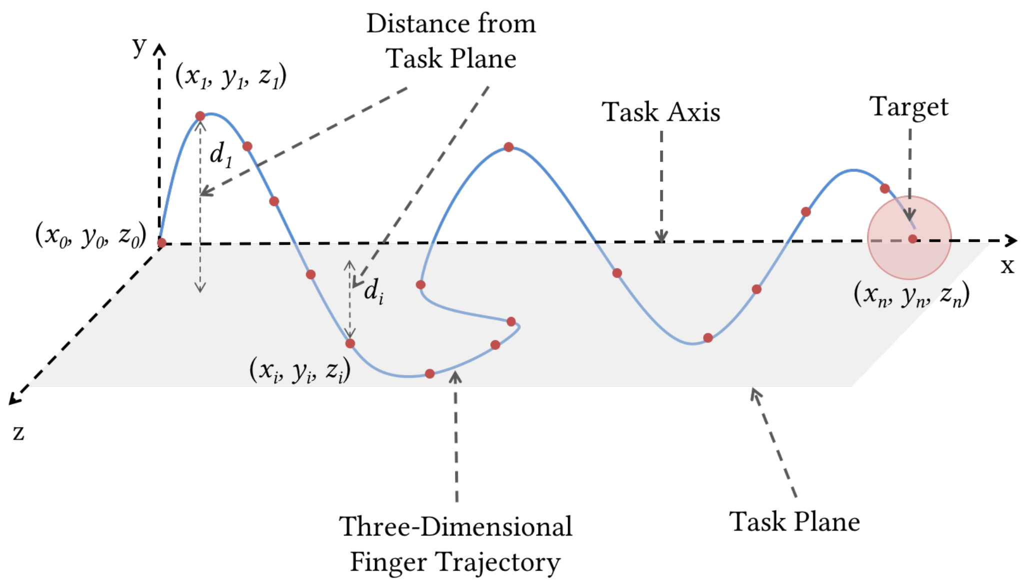


Figure 4.4 Fingertip locations (x_i, y_i, z_i) in a three-dimensional trajectory are shown with red dots. Distances between the fingertip locations and the task planes are applied to calculate movement offset (MO), movement error (ME), and movement variability (MV).

These continuous measures are illustrated in Figure 4.4, where $(x_0, y_0, , z_0)$, (x_1, y_1, z_1), $\ldots$, (x_i, y_i, z_i), $\ldots$, (x_n, y_n, z_n) are the fingertip locations from a selection trajectory. The mathematical definitions of MO, ME, and MV are presented in Eq. 4.1 – 4.3, respectively. In these equations, the signed distance between a fingertip location (x_i, y_i, z_i) and the task plane is denoted with d_i, the absolute value of d_i is denoted with $|d_i|$, and the number of available fingertip locations are denoted with n. In Eq. 4.3, MO represents the movement offset (defined in Eq. 4.1).

$$MO = \frac{\sum_{i=0}^{n} d_i}{n} \tag{4.1}$$

$$ME = \frac{\sum_{i=0}^{n} |d_i|}{n} \tag{4.2}$$

$$MV = \sqrt{\frac{\sum_{i=0}^{n} (d_i - MO)^2}{n-1}} \tag{4.3}$$

Path Axis Ratio (PAR)

Path axis ratio, introduced in Keates and Trewin (2005), was recast as the sum of the three-dimensional distances between adjacent fingertip locations divided by the length of the task axis (see Figure 4.5).

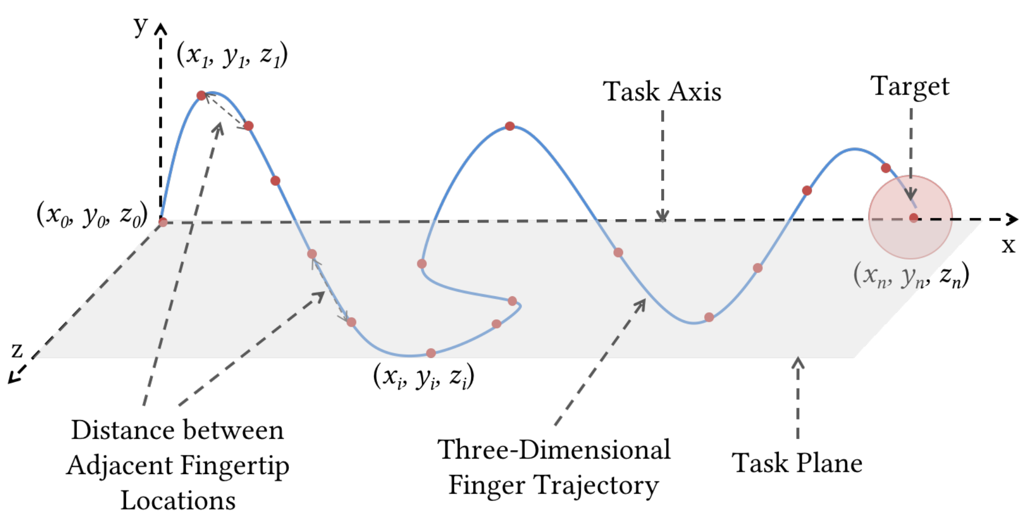


Figure 4.5 Fingertip locations (x_i, y_i, z_i) in a three-dimensional trajectory are shown with red dots. Three-dimensional distances between adjacent fingertip locations are applied to calculate the path axis ratio (PAR).

Pause Frequency, Duration, and Location Distance(PF, PD, PLD)

We define a pause when the fingertip velocity is less than 5 mm/second. The following pause-related measures: pause frequency (PF), pause duration (PD), and pause location distance (PLD) were directly taken from Hwang et al. (2005) as it is a straight-forward mapping from two-dimensional to three-dimensional interaction. The pause frequency (PF) and duration (PD) count the number of pauses per trial, and the mean duration (measured in milliseconds (ms)) of all pauses per trial, respectively. The pause location distance (PLD) represents the mean distance between the fingertip locations of all pauses and the target center. The PLD is reported in millimeters (mm).

Peak and Mean Speed (SP and SM)

We included two speed-related measures: peak speed (SP) and mean speed (SM). Peak speed (SP) is the highest fingertip velocity observed in a trial and was included from Hwang et al. (2005). Although Hwang et al. (2005) measured the peak speed per submovement, we measured the peak speed per trial to be consistent with other measures. We introduced a new measure mean speed (SM) that is the mean of all fingertip velocities within a trial. Both measures are reported in millimeter/seconds.

Rotation: Mean Pitch, Yaw, and Roll (RP, RY, and RR)

Mean pitch (RP), yaw (RY), and roll (RR) are mean finger rotation around the x-, y-, and z-axis, respectively, considering the task axis aligns with the x-axis (see Figure 4.6). The rotations are signed rotations, where a counter-clockwise rotation holds a positive value and a clockwise rotation holds a negative value. All rotation measures are reported in degrees, and were developed for touch interaction by Holz and Baudisch (2011).

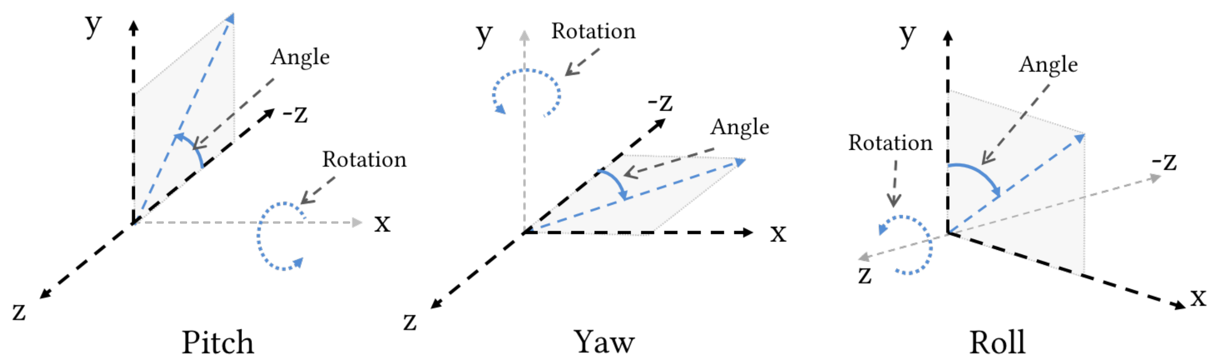


Figure 4.6 Finger pitch, yaw, and roll. All angles and rotation directions are positive.

4.2.2 Finger Trajectory Measure Implications

Higher counts in movement direction changes along all axes (DC-X, DC-Y, DC-Z), along with higher task plane crossing (TPC), and path axis ratio (PAR) suggest that a number of corrective submovements took place due to overshoots or undershoots, during the target selection. Higher values in task plane crossing (TPC), path axis ratio (PAR), movement offset (MO), movement error (ME), and movement variability (MV) reflect higher deviation from the task axis. Like MacKenzie et al. (2001), we included all three movement deviation measures: movement offset (MO), error (ME), and variability (MV). Although they are similar, they have been associated with different types of selection behavior. For example, if the finger distances (d_i) with similar magnitudes occur in both above and below the task plane with a higher number of task plane crossing (see Figure 4.7(left)), the signed distances at both sides of the task plane may cancel each other, and the resulting low movement offset (MO) may not reflect high deviations that happened at the both sides of the task plane. Both movement error (ME) and movement variability (MV) have a better advantage over movement offset (MO) in such cases because of considering the absolute distances from the task plane, instead of considering the signed distances (see Figure 4.7(left)). On the other hand, if the trajectory is relatively smooth (i.e., with less variation in the fingertip distances), but fingertips are far from the task plane (i.e., with larger d_i), such behavior will not be detected by movement variability (MV), but will be detected by both movement error (ME) and offset (MO), if task plane crossing count is low (see Figure 4.7(right)). Frequent long pauses (PF and PD) and low peak and mean speed (SP and SM) results in longer task completion time that eventually lower the performance throughput. Higher pause location distance (PLD) indicates pauses were taken not only for target verification (i.e., near the target boundaries). Pauses taken throughout the selection trajectories suggest smaller submovements were taken during the selection tasks. Higher mean finger rotations, mean roll (RR), pitch (RP), and yaw (RY), reflects the need of twisting the pointing finger to aim correctly to the targets. By definition, all of these finger trajectory measures represent selection behaviour that can impact the performance throughput of a selection task. In the remaining subsections of this chapter we present a study that investigates how do these finger trajectory measures influence the performance throughput in touch input.

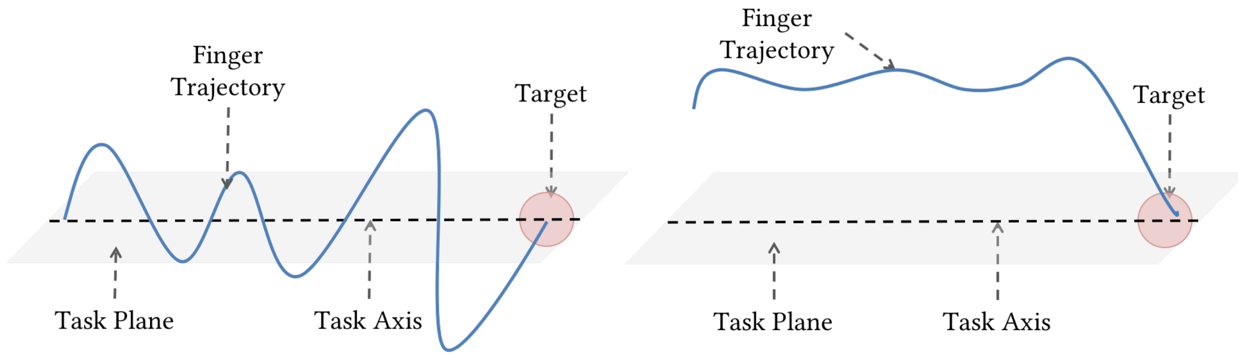


Figure 4.7 Difference between movement offset (MO), movement error (ME), and movement variability (MV). The left finger trajectory has high movement error and movement variability, but low movement offset. The right finger trajectory has high movement error and movement offset, but low movement variability.

4.3 Method and Materials

We generally followed the same study methodology as the error analysis study that was presented in Chapter 3. Instead of using a touchscreen smartphone (screen size: 74.19 mm × 131.89 mm), finger trajectory data were collected by a custom-built tool that combined a touchscreen tablet (screen size: 180.62 mm × 135.47 mm) and motion sensors. Like the error analysis study, participants were asked to perform a two-dimensional Fitts's task-like selection task (Fitts, 1954; Ren & Moriya, 2000) in a controlled lab environment. Notably, we added an additional target width and a target amplitude in the selection task. To understand the overall reliability of the finger trajectory measures for explaining lower performance throughput in touch input, we analyzed participant data from both older and younger adults. We used the same dataset in the trajectory analysis study presented in Chapter 5, where, we analyzed participant data in age-group level to understand their age-related differences. We also examined the relationships between the finger trajectory measures and throughput in individual age groups in Chapter 5. The following subsections outline the study methodology for both Chapters 4 and 5. Therefore, some subsections contain details on data from individual age groups that are not relevant to this study, but are relevant to the study methodology (Section 5.2) of the finger trajectory analysis study presented in Chapter 5.

4.3.1 Participants

We recruited 16 older adults (7 female and 9 male, aged 66–81, with a mean(SD) of 73.44(4.23) years) and 16 younger adults (9 female, 6 male, and 1 undisclosed, aged 20–34, with a mean(SD) of 26.38(4.19) years). All participants self-reported being right-handed, with no motor impairments to their right hand, and having normal or corrected-to-normal vision, as per the inclusion criteria from the call for participation documents. None of these individuals participated in the error analysis study that was reported in Chapter 3. Participants were highly educated, with most of the older adults (14/16) reported holding at least a bachelor's degree, and all of the younger adults reported either holding (13/16) or being enrolled (3/16) in a bachelor's degree program. Ten older adults rated their expertise with touchscreen devices as moderate or higher, 5 rated it as basic, and 1, as less than basic. All younger adults rated their experience as moderate or higher. The self-reported average usage time of touchscreen devices per week of older adults was 13.47 hours (SD: 19.67), and that of younger adults was 37.19 hours (SD: 19.38).

To assess participants' sensory-perceptual-motor skills, and their ability to understand

English instructions (Strauss et al., 2006), we applied the same three standardized neuropsychological tests as the error analysis study: Digit Symbol Substitute Test (DSST), Letter Set Test (LST), and North American Adult Reading Test (NAART). Older adult participants had lower perceptual speed (DSST) and lower fluid intelligence (LST), consistent with normative data on age-related differences (Strauss et al., 2006). On the DSST, older adults scored a mean of 50.25 out of 84 (SD: 15.38), while younger adults scored 62.56 (SD: 10.61). On the LST, older adults averaged 13.66 out of 30 (SD: 6.30), while younger adults averaged 19.00 (SD: 5.59). The first 15 words of North American Adult Reading Test (NAART) were used to confirm participants' ability to understand and follow the study session instructions. All participants, both older and younger, had satisfactory NAART scores of 13/15 or higher. We did not find any outlier participant data in these neuropsychological tests. All neuropsychological test results aligned with the results from the error analysis study.

4.3.2 Apparatus

Collecting finger trajectory data was challenging, because the types of handheld touchscreen devices we are interested in studying, do not provide trajectory data. Trajectory data from indirect input devices (e.g., mouse) can be directly collected from the system logs, as the trajectories remain in the two-dimensional device planes. The tracking devices implanted inside the inductive pens can capture the projected two-dimensional trajectories on the device plane. To track such trajectory data, inductive pens need to be either in-touch, or remain very close to the device screen. On the contrary, commercial touchscreen devices natively capture finger trajectory data, only when the finger is touching the device screen. However, a major portion of the three-dimensional finger trajectories remain mid-air, when finger is not touching the device. Without these data, finger trajectory analysis is incomplete. To collect the entire finger trajectory data, we required an apparatus that could collect trajectory data when the finger was touching the touchscreen device, and also when the finger was in the air (i.e., not in contact with the touchscreen device).

To collect the mid-air finger trajectory data, we custom-built a finger trajectory data collection tool[3] by augmenting a touchscreen tablet with an external motion-capturing device, named LEAP motion controller. The LEAP motion controller measures 76.2 mm × 30.48 mm × 12.7 mm, and is specifically designed to track close-range hand and finger movements (Marin et al., 2014; Ramani, 2015). In particular, this device tracks the skeletal structures of hands and fingers (including the index finger that is used in the target selection task), and records their exact locations in a three-dimensional Cartesian space, in real-time[4]. Although the LEAP motion technology has not been previously used to collect finger trajectory data from touch input, this technology has been tested with a wide-range of applications, such as hand gesture recognition (Marin et al., 2014), sign language recognition (Mapari & Kharat, 2016; Potter et al., 2013), mid-air pointing (Cabreira & Hwang, 2018), human-robot interaction (Bassily et al., 2014; Guerrero-Rincon et al., 2013), creating and manipulating three-dimensional shapes (Huang & Rai, 2018; Jailungka & Charoenseang, 2018; Ramani,

[3]Description of this three-dimensional finger trajectory data collection tool appeared as: Sultana, Xu, and Moffatt (2018).

[4]Visit https://www.ultraleap.com for more details on the LEAP motion controller.

2015), three-dimensional point cloud dataset generation and annotation (Bacim et al., 2014), and autonomous driving (Manawadu et al., 2001). A major advantage with LEAP motion controller is that it does not require additional markers or wearable sensors on the fingers as external sensor-based systems do (Rautaray & Agrawal, 2015; Vuletic et al., 2019). Some prior studies have suggested that camera- or infrared-based trackers (like LEAP motion controllers) are more suitable for older adults than the ones that require external markers or sensors, which can be uncomfortable, distracting, or influence movement (Bhuiyan & Picking, 2011; Carreira et al., 2017; Nazemi et al., 2011). Moreover, it is optimized for capturing small close-ranged finger and hand gestures, and is thus better for capturing small finger movements within a short distance (Potter et al., 2013; Vuletic et al., 2019). Some prior works have raised concerns about the accuracy and reliability of the LEAP motion controller. However, those issues emerged because of having multiple fingers in very close proximity (Marin et al., 2014), encountering occlusion due to the palm (Huang & Rai, 2018), or requiring to capture very complex gestures with different parts of the hand (fingers, palm, and wrist) moving in different planes (Guerrero-Rincon et al., 2013; Marin et al., 2014; Potter et al., 2013; Xi et al., 2014). Finger movements from target selection tasks are relatively simpler than any of these tasks and gestures.

Data Collection

Our custom-built tool used an HTC Nexus 9 touchscreen tablet, running the Android 7.1.1 operating system. The screen resolution was 2048 $\times$ 1536 pixels (with 4:3 aspect ratio) and the screen size was 180.62 mm × 135.47 mm, for a 0.088 mm pixel size (PPI = 288). The fingertip coordinates and system timestamp information of all finger touchdown and lift-up events were recorded. In addition, coordinates of the centers of the start button, and the targets were stored for calculating the finger trajectory measures. All fingertip touchdown and lift-up coordinates were measured in pixel. The data collection software for the tablet was developed with Android Studio.

The LEAP motion controller was equipped with two built-in infrared cameras and three infrared LEDs that provided a combination of a vision- and proximity-based movement tracking system. Although the LEAP motion controller could not be directly connected to the tablet, it was small enough to be placed in front of the tablet such that finger movements from the selection tasks, performed on the tablet, remained within the range of that motion-tracking device. When placed on top of a horizontal surface, the LEAP motion controller provided 150° and 120° fields of view in the x-y plane, and y-z plane, respectively – that covered a 609.6 mm × 342.9 mm × 300 mm space. Data collection rate of the LEAP motion controller was 100 frames/second. As the LEAP motion controller required an external computer for data processing and storage, we connected it to a 2.9 GHz MacBook Pro laptop with Intel Core i7 processor, running MAC OS X Yosemite 10.10.5. The LEAP motion controller collected the system (laptop) timestamp, fingertip coordinates, finger movement directions, fingertip velocity, and finger angles, in three dimensions. All coordinates, velocities, and angles were measured in millimeters (mm), millimeters/second (mm/s), and radians, respectively. The data collection software for the LEAP motion controller was developed with the

JAVA LEAP motion SDK, in Eclipse development environment.

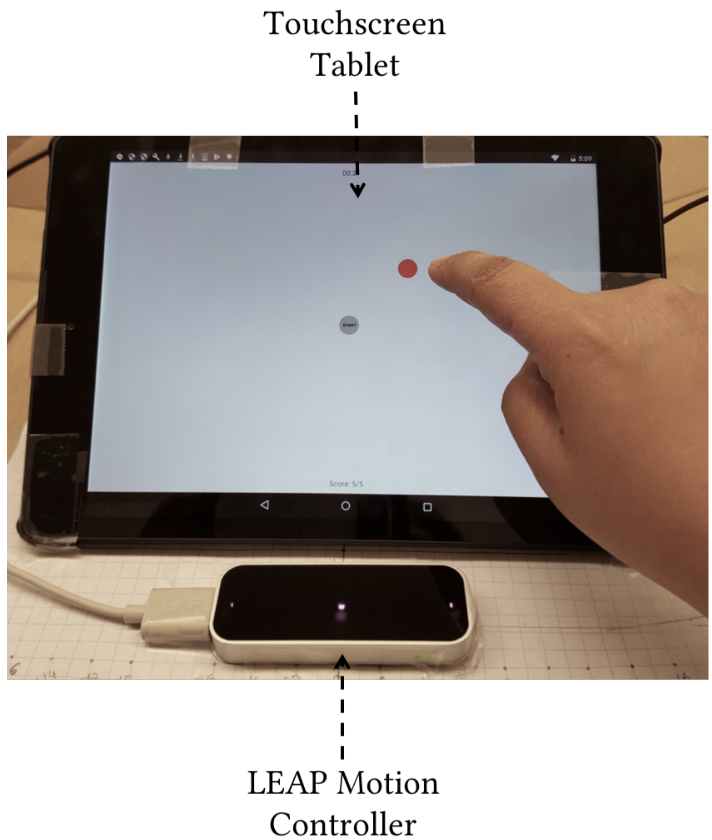


Figure 4.8 Three-dimensional finger trajectory data collection tool. The touchscreen tablet is reclined in 45-degree angle, and the LEAP motion controller is in front of the tablet. Both devices are fixed with their origins aligned.

During data collection, the tablet was placed on a table in the landscape orientation, and was tilted at 45° angle. We carefully positioned the LEAP motion controller relative to the tablet to minimize the potential for occlusion and out of the range movements. We also fixed the positions of the tablet and the LEAP motion controller such that the center of the tablet aligned with the center of the LEAP motion controller (see Figure 4.8). Positions of the both devices were fixed to maintain data accuracy (more details are available on *Fingertip*

Location Mapping Between Devices, page 95). We also adjusted the room lighting to ensure that finger is visible to the LEAP motion infrared cameras and LEDs.

Fingertip Location Mapping Between Devices

The tablet and the LEAP motion controller in our custom-built tool had their own independent coordinate systems. The tablet collected the location data in a two-dimensional coordinate systems, with the origin (0, 0) located at the top-left corner of the touchscreen (see Figure 4.9). The x-coordinates increased towards right, and the y-coordinates increased downward. The distance was measured in pixels. On the contrary, the LEAP motion controller collected the location data in a right-handed three-dimensional coordinate system, with the origin (0, 0, 0) located at the center of the top surface of the device (see Figure 4.9). The x-, y-, and z-coordinates increased towards right, up, and forward (opposite direction from the tablet), respectively. The distance was measured in millimeters. Because of these independent coordinate systems, we computed the relative mapping between each device's origin to create a common set of coordinates. We used this common set of coordinates to calculate the finger trajectory measures.

We manually calculated the tablet center coordinates to the LEAP motion coordinate system. With the system in the fixed positions (i.e., the tablet tilted at 45° angle and the LEAP motion controller's center aligned with the tablet's center, see Figures 4.8 and 4.9), we used a ruler to manually measure the x, y, and z distances between the center of the tablet, and the center of the LEAP motion controller (which is also the origin of its

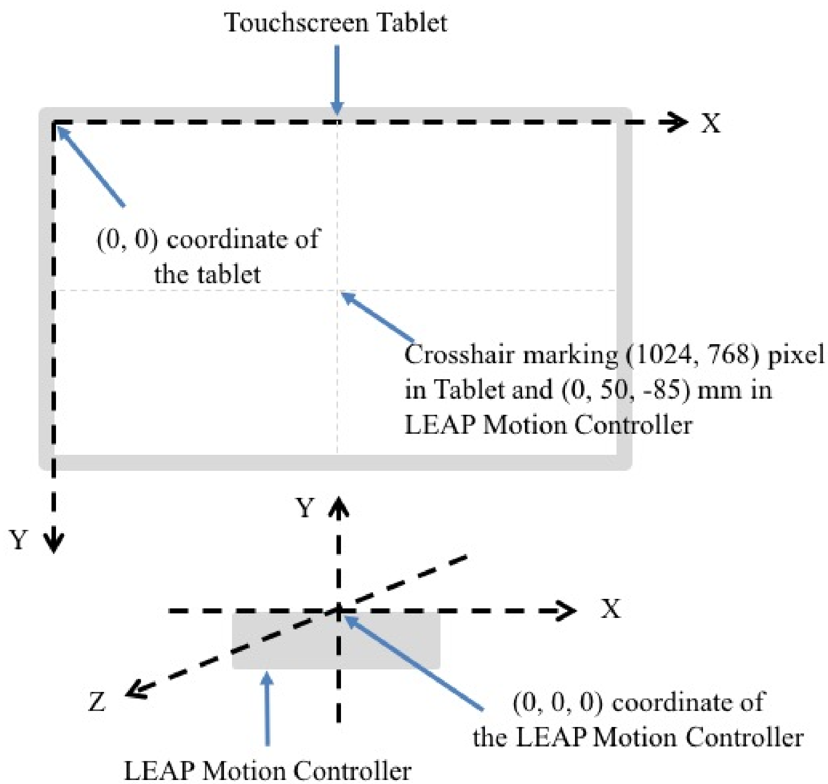


Figure 4.9 Coordinate Systems of the touchscreen tablet and the LEAP motion controller. The coordinate origin of the tablet is at the top-left corner of the device, and same for the LEAP motion controller is at the center of the top surface of the device. The crosshair at the center of the tablet marks the (1024, 768) pixel coordinate in tablet and (0, 50, -85) mm coordinate in the LEAP motion controller.

coordinate system) in millimeters. We took manual measurements because human fingertips are not precise enough to pinpoint the exact center of the tablet. We acknowledge that manual measurement can introduce errors in the coordinate system. However, these errors are generally smaller than the precision of human fingertips. Our manual measures found the x, y, and z distances between the centers to be 0, 50, and 85 millimeters, respectively. Thus, the coordinates of the center of the tablet (1024, 768) mapped to the (0, 50, -85) coordinate of the LEAP motion (recall that movement along the z axis was negative in the direction toward the tablet as shown in Figure 4.9). We also validated our manually measured coordinates of the tablet center by collecting fingertip locations from the LEAP motion controller, while three younger adult participants (1 male, 2 female) selected a crosshair, marking the center of the table (as shown in Figure 4.9). Once we confirmed the location of the tablet center in LEAP motion coordinate system, we derived the following equations: Eq. 4.4 and Eq. 4.5 to map the tablet coordinates to LEAP motion coordinates. Both Eq. 4.4 and Eq. 4.5 incorporated the pixel-mm conversion (1 pixel = .088 mm). The 45° tablet angle, and the 50 mm distance in y-coordinates between the two devices were included in Eq. 4.5.

$$LeapX = (TabletX - TabletCenterX) * 0.88\,mm \tag{4.4}$$

$$LeapY = [-(TabletY - TabletCenterY) * 0.88\,mm] * \sin(TabletAngle)] + 50\,mm \tag{4.5}$$

Data Integration

Integrating trajectory data of the same trial from two different data collection sources (i.e., touchscreen tablet and LEAP motion controller) was particularly challenging, mainly because these two devices could not be directly connected. Although assigning trial identification numbers (trial ID) to each trial in real time was an obvious choice, it was only a viable option for the tablet, but not for the LEAP motion controller. Because the LEAP motion collected a stream of data at a fixed time interval, without the knowledge of beginning and ending of a trial, assigning trial IDs to the LEAP data in real time was not possible.

As an alternative method, we considered synchronizing system timestamps from both devices[5] to correctly identify and label trajectory data from the same trial. Synchronizing timestamps from two devices was also challenging because trials from the selection task took fraction of seconds such that the event logs from both devices needed to be merged with millisecond precision. It was crucial to have the same clock speed in both devices (i.e., having the exactly same timestamps) to correctly identify trajectory data from the same trial. However, our data collection devices had different clock speeds. To address this challenge, we opted for collecting timestamps from a single source, by setting up a server on the laptop that was connected to the LEAP motion controller. This server worked as an intermediary between the tablet and the LEAP motion controller. Instead of recording its own timestamps, the tablet requested the timestamps from the laptop via the server over a Wi-Fi connection. All timestamps collected over the Wi-Fi connection were adjusted for the round-trip response delays between the tablet and the server.

We recorded the finger lift-up event timestamps of the start button and the target selection from the tablet in real time and adjusted the round-trip response delays. These two finger lift-up events marked the beginning and the ending of a trial, respectively. During post-processing, we extracted all data frames from the LEAP motion data stream that were

[5] Timestamps for the LEAP motion controller were collected from the laptop it was connected to.

collected between these two aforementioned timestamps from the tablet. We labeled these LEAP data frames with the same trial ID as in the tablet (see Figure 4.10). We developed the data integration software with Python, using the PyCharm development environment. The server connections were implemented in JAVA with the IntelliJ IDEA environment.

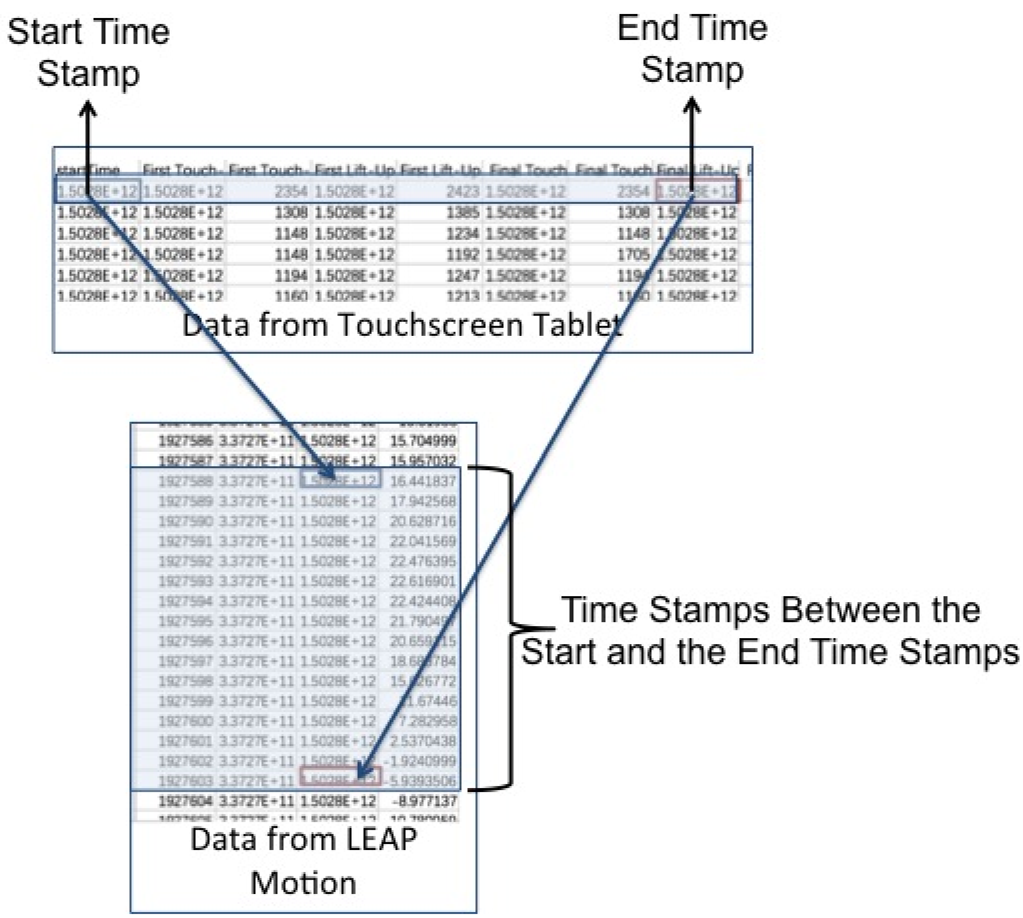


Figure 4.10 Identifying trials in the LEAP motion data from matching timestamps. Labeling all frames from the LEAP data taken between the start and end timestamps collected from the touchscreen data.

4.3.3 Task

Participants completed a two-dimensional Fitts's task-like target selection task (see Figure 4.11), consistent with prior work (Ren & Moriya, 2000) and the error analysis study from Chapter 3. A seven-millimeter wide circular start button appeared at the center of the screen that marked the beginning of each trial. Once the participants successfully selected the start button, a red circular target appeared at one of the three predefined target amplitudes (20 mm, 30 mm, and 40 mm), four predefined target widths (4.88 mm, 7.22 mm, 9.22 mm, and 12.22 mm), and eight predefined movement angles (0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°) from the center of the start button. Target widths (size), amplitudes (distance), and angles (location) were chosen based on the error analysis study from Chapter 3. In the error analysis study, we observed high error rates in older adults, even with the largest targets (9.22 mm)[6]. We added a larger width (12.22 mm) and a larger amplitude (40 mm) in this study.

Each combination of amplitude, width, and angle appeared exactly once per block of 96 trials, in a randomized order. Participants were instructed to select the targets with their right index finger, as quickly and accurately as possible. If they missed a target, they continued with the trial until successfully selecting it to motivate a more realistic effort. However, analysis was conducted based on data only up to the first selection attempt, regardless of correctness. Before participants started the task, they were asked to complete at least one practice block of twelve trials. Participants started the task once they felt

[6]Error rates in the error analysis study for older adults varied between 9.74% to 62.40% (see Figure 3.7).

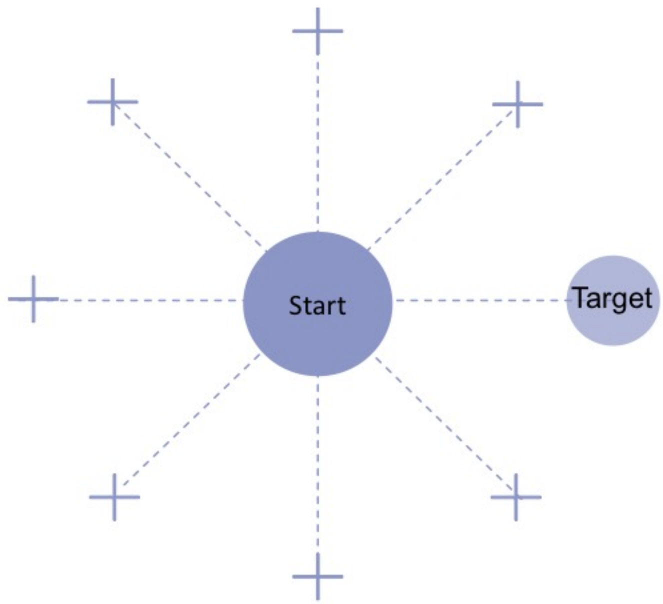


Figure 4.11 Two dimensional Fitts's task showing 8 possible target locations (angles in counter clockwise direction) relative to the Start button at the center of the screen. The circle labeled Target shows a sample target at the 0° angle.

comfortable with it. No one asked for more than one practice block. The two-dimensional selection task was carried out in four blocks, each containing 96 trials with a mandatory minimum 30-second break at the halfway point (after the 48^{th} trial) of each block. We introduced this mandatory break to avoid fatigue during a block. In addition, short breaks of at least one minute were given between the blocks as needed. Participants were allowed to ask questions between trials. A timer was displayed at the top of the screen and a scoreboard at the bottom to give feedback on movement time and accuracy.

4.3.4 Design

We applied a 2 (age groups) × 4 (blocks) × 4 (target widths) × 3 (movement amplitudes) × 8 (movement angles) mixed design with all factors except for age as within-subjects factors. Each of four block consisted of 96 trials, containing each unique combination of width × amplitude × angle exactly once, presented in a random order. We collected a total of 384 trials per participant and 6,144 trials per age group. In total, we collected 12,288 trials from 32 participants.

4.3.5 Procedure

Each session started with a brief introduction, along with a review of informed consent. Participants then completed a background questionnaire covering demographic data and their touchscreen experience, followed by the DSST. Then, they were introduced to the two-dimensional target selection task with a brief discussion and a practice session. Once comfortable with the task, they completed all four blocks of the task, while the researcher took observational notes on their target selection behavior. After completing the selection task, participants answered a short questionnaire about their overall experience with the task. They were then asked to read the first 15 words from the NAART, followed by completing the LST. They finished the study with a short debrief and a wrap-up. We designed the experiment to fit within a single session aiming for no more than 90 and 60 minutes for older and younger participants, respectively, similar to the error analysis study from Chapter 3. Everyone finished their tasks within their allocated time. Older and younger participants received an honorarium of $15 and $10, respectively. All procedures of this study were reviewed and approved by our institution's Research Ethics Board prior to the commencement of the study. A copy of the Ethics Approval Certificate is included in Appendix E.

4.3.6 Measures

Finger Trajectory Measures. We report all sixteen three-dimensional finger trajectory measures that were described in Section 4.2. The measures and their corresponding units are: direction changes along the x-, y-, and z-axis (DC-X, DC-Y, DC-Z), task plane crossing (TPC), movement offset (MO, mm), movement error (ME, mm), movement variability (MV, mm), path axis ratio (PAR), pause frequency (PF), pause duration (PD, ms), pause location distance (PLD, mm), peak speed (SP, mm/second), mean speed (SM, mm/second), mean pitch (RP, degree), mean yaw (RW, degree), and mean roll (RR, degree). Direction changes along all axes (DC-X, DC-Y, DC-Z), task plane crossing (TPC), movement offset, error, variability (MO, ME, MV), and path axis ratio (PAR) were calculated from the three-dimensional fingertip locations that were collected from the LEAP motion controller. Pauses were marked in the trajectories when fingertip velocity collected from the LEAP motion controller was less than 5 mm/sec. Both peak and mean speed (SP and SM) were directly collected from fingertip velocity data provided by the LEAP motion controller. Finger rotations pitch, yaw, and roll (RP, RY, RR) were provided by the LEAP motion controller, with the respect to the device. We mapped the finger rotations with the respect to the task axis, and converted the units from radians to degrees. Among these measures, movement error and offset (ME, MO), pause duration and location distance (PD, PLD), mean speed (SM), and finger pitch, yaw, and roll (RP, RY, RR) are reported as the mean value per trial. The rest of the measures are reported as count or value per trial.

Performance Throughput. We calculated the performance throughput (IP) of the selection tasks by taking the ratio of the index of difficulty (ID) and the movement time (MT) as in Eq. 4.6. Performance throughput was measured in bits/second. Index of difficulty (ID) was calculated according to Eq. 4.7, where D and W represented the target amplitude and width, respectively. Movement time (MT) was the elapsed time between selecting the start button and the first attempt to select the target (same as Chapter 3), and was measured in seconds.

$$IP = ID/MT \tag{4.6}$$

$$ID = log_2[\frac{D}{W} + 1] \tag{4.7}$$

$$MT = a + b * ID \tag{4.8}$$

$$W_e = \sqrt{2\pi e}\sigma \tag{4.9}$$

Recent touch input studies using representative target sizes (i.e., small targets similar to those on mobile devices) have opted for nominal width (W) over effective width (W_e, see Eq. 4.9) for the index of difficulty calculation (Findlater et al., 2013; Findlater & Zhang, 2020). While the effective width was introduced to compensate for under-utilization of target widths for mouse input (MacKenzie, 1992; Soukoreff & MacKenzie, 2004; Welford, 1968), the imprecise fingertips (compared to mouse cursors) typically generate higher selection endpoint variability in touch input that can result in effective widths that are larger than the nominal widths (Bi et al., 2013; Cockburn et al., 2012; Holz & Baudisch, 2011; Sasangohar et al., 2009). Moreover, applying effective width that is larger than the nominal width can result in very low $ID - MT$ model fit for Eq. 4.8, particularly with smaller targets (Bi et al., 2013).

Both of our studies in Chapter 3 and in this chapter examined representative targets that are similar to the size of the targets found in commercial touchscreen devices. These targets were relatively smaller than targets that were used in prior works on touch and mouse input (Findlater et al., 2013; Keates & Trewin, 2005). The study presented in Chapter 3 demonstrated higher selection endpoint variability with touch input in older adults. Our preliminary data analyses in this study found that the effective width overestimated the nominal width in both age groups (between 1.18 – 8.13 times for older adults and between 1.25 – 4.14 times for younger adults, see Table 4.2 for details). Moreover, the $ID - MT$ model fits for Eq. 4.8 were $r^2 = 0.15$ for all participants, $r^2 = 0.00$ for older adults, and $r^2 = 0.21$ for younger adults, when effective width was applied (see Figure 4.12). Because of such over compensating effective widths, and very low $ID - MT$ model fits in our study data, we opted for applying the nominal target width, instead of the effective width for our index of difficulty calculation in Eq. 4.7. After applying the nominal target width in Eq. 4.7, our index of difficulty (ID) for all twelve amplitude-width combinations (3 amplitudes $\times$ 4 widths) ranged between 1.40 to 3.20 bits (see Table 4.5), and achieved a satisfactory $ID - MT$ model fit for Eq. 4.8 (all participants: $r^2 = 0.96$; older adults: $r^2 = 0.94$; younger adults: $r^2 = 0.96$; see Figure 4.13).

Table 4.2 Ratio of effective and nominal width of older and younger adults across target amplitudes and widths.

		Older Adults		Younger Adults	
Amplitude (mm)	**Width (mm)**	**Effective Width (mm)**	**Effective Width / Width**	**Effective Width (mm)**	**Effective Width / Width**
20	4.88	18.19	3.73	17.06	3.50
20	7.22	20.55	2.85	13.84	1.92
20	9.22	13.67	1.48	17.24	1.87
20	12.22	14.43	1.18	15.23	1.25
30	4.88	24.02	4.92	10.43	2.14
30	7.22	20.87	2.89	23.49	3.25
30	9.22	22.99	2.49	20.02	2.17
30	12.22	19.04	1.56	15.81	1.29
40	4.88	39.66	8.13	20.18	4.14
40	7.22	20.04	2.78	28.10	3.89
40	9.22	24.34	2.64	21.30	2.31
40	12.22	26.43	2.16	20.72	1.70

4.3.7 Data Cleaning

At the beginning of the data cleaning process, we tested whether any participant's mean movement time and mean error rate were three or more standard deviations away from

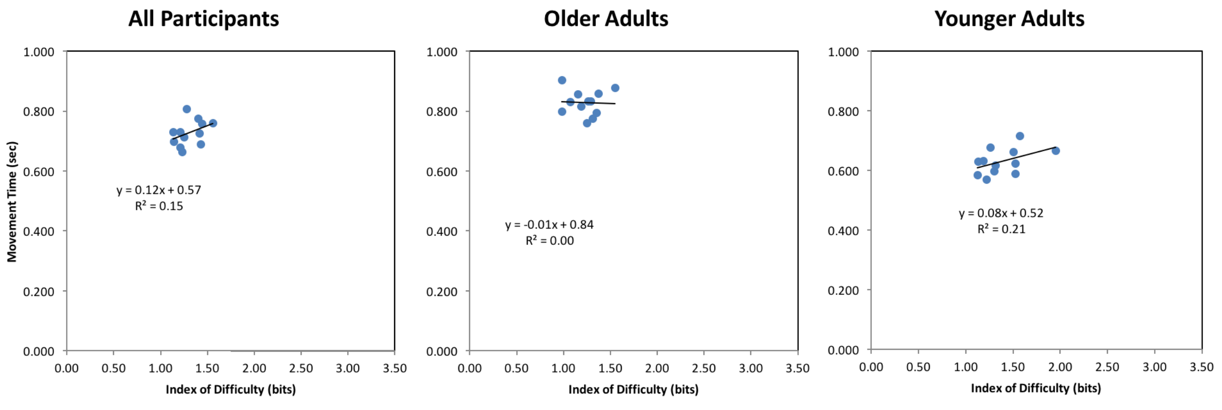


Figure 4.12 Fitts's model across all 3 amplitude × 4 width combinations for all participants, older adults, and younger adults with effective width.

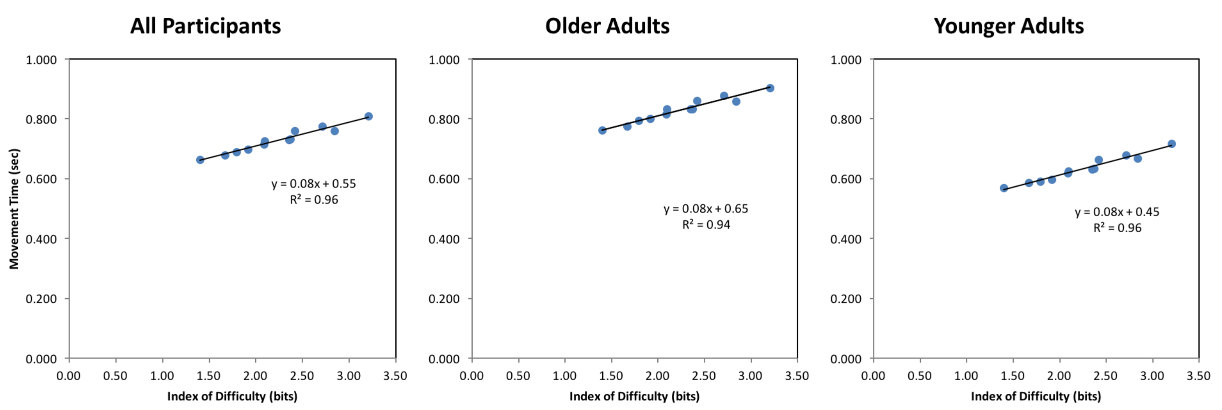


Figure 4.13 Fitts's model across all 3 amplitude × 4 width combinations for all participants, older adults, and younger adults with nominal width.

their age group mean, i.e., an outlier in that age group. No such outliers were found. We then conducted two steps of trial-level data cleaning. In the first step, we excluded trials with movement time more than three standard deviations away from the age group's mean movement time as these trials might not reflect rapid aimed selections (Findlater & McGrenere, 2010). Out of 12,288 trials (6,144 in each age group), we removed 200 trials (3.26% of 6,144 trials) from older adults and 45 trials (0.73% of 6,144 trials) from younger adults, 245 trials (1.99% of 12,288 trials) in total. After the removal, we had 12,043 trials in total (5,944 trials from the older, and 6,099 trials from the younger adults).

In the second step, we additionally removed trials with insufficient (two or less) fingertip location data points because some of our trajectory measures required at least three such data points to compute. Missing fingertip location data points occurred, if the participants' index finger was outside the range of the LEAP motion at the point of sampling. We removed 918 trials in total (7.62% of 12,043 trials) on this account, among which, 503 trials (8.46% of 5,944 trials) were removed from older adults, and 415 trials (6.80% of 6,099 trials) were removed from younger adults. After this step, 5,441 trials from older adults, and 5,684 trials from younger adults, 11,125 trials in total remained for the final data analysis. Although, the minimum number of required data points, three, provides very little insight into the trajectory, we chose this cut-off point conservatively to minimize the number of trials to be removed in the second step. Analysis of the data point distribution per trial showed that the cut-off at three data points had negligible effect on our whole dataset. On average, older and younger adults had 69 and 50 data points per trial, respectively. This sampling rate was comparable with prior work (MacKenzie et al., 2001), where the mouse data sampling rate was 40 data frames/second and the mean movement times for mouse were less than a second, implying an average of less than 40 data points per trial. The mean, standard deviation (SD), median, and inter quartile range (IQR) of fingertip location data points per trial for older and younger adults are reported in Table 4.3.

Table 4.3 The mean, standard deviation (SD), median, and inter quartile range (IQR) of the number of available data points (fingertip locations), across age groups.

Age Group	**Mean**	**SD**	**Median**	**IQR**
Older Adults	68.9	24.8	64	34
Younger Adults	49.8	17.2	45	19

After the two-step data cleaning, the remaining 11,125 trials were fairly evenly distributed across each of the twelve target amplitude-width (3 amplitudes × 4 widths) combinations, ranging from 915 to 941 for all participants, from 442 to 461 for older adults, and from 462 to 480 for younger adults. See Table 4.4 for the trial distribution in each individual amplitude-width combination.

4.4 Results

In this section, we present the results from this study that examined the reliability of applying the finger trajectory measures to reflect on overall low performance throughput (*RQ2.1* and *RQ2.2*). To answer *RQ2.1*, we evaluated the relationships between the finger trajectory measures and throughput. In particular, we examined how any changes in the finger tra-

Table 4.4 Trial distribution across age groups in each individual amplitude-width combination. All = All Participants, OA = Older Adults, YA = Younger Adults.

Amplitude (mm)	**Width (mm)**	**ID**	**Number of trials (All)**	**Number of trials (OA)**	**Number of trials (YA)**
20	4.88	2.35	921	455	466
20	7.22	1.91	918	456	462
20	9.22	1.66	930	454	476
20	12.22	1.40	925	458	467
30	4.88	2.84	934	454	480
30	7.22	2.37	941	461	480
30	9.22	2.09	932	453	479
30	12.22	1.79	922	450	472
40	4.88	3.20	933	455	478
40	7.22	2.71	915	442	473
40	9.22	2.42	926	452	474
40	12.22	2.10	928	451	477
Total			**11,125**	**5,441**	**5,684**

jectory measures affected the performance throughput of selection tasks. To answer *RQ2.2*, we analyzed the relationships among the finger trajectory measures, i.e., we examined how changes in one measure affected other measures.

Results from our relationship analysis are consistent with prior work (MacKenzie et al., 2001) and are presented in Section 4.4.1. Our analysis demonstrated moderate to strong relationships between a subset of finger trajectory measures and throughput, where, high values in these finger trajectory measures implied low throughput. Our analysis also identified very strong relationships among a number of finger trajectory measures. These strong relationships highlight their combined contributions to throughput, but obscure their independent contributions to throughput (MacKenzie et al., 2001). In Section 4.4.2, we analyzed the independent contributions of each finger trajectory measures to throughput. We also further analyzed the independent contributions of the finger trajectory measures to each other. From this point on, we will refer to such analyses of individual contributions of finger trajectory measures to throughput, and to each other as *dependency analysis*. Both relationship and dependency analyses, presented in this chapter, used the data collected from all thirty-two participants (i.e., we included data from both older and younger adults). Relationship and dependency analyses for individual age groups are presented in Section 5.3.3 of Chapter 5. The index of difficulties, mean movement times, and mean performance throughput across all twelve amplitude-width combinations (3 amplitudes $\times$ 4 widths) from all participant data are presented in Table 4.5.

Table 4.5 Index of Difficulty (ID), mean movement time (MT), and mean performance throughput (IP) for all participants across target amplitudes and target widths.

Amplitude (mm)	**Width (mm)**	**Index of Difficulty (bits)**	**Mean Movement Time (seconds)**	**Mean Throughput (bits/seconds)**
20	4.88	2.35	0.730	3.22
20	7.22	1.91	0.698	2.74
20	9.22	1.66	0.678	2.45
20	12.22	1.40	0.664	2.11
30	4.88	2.84	0.760	3.74
30	7.22	2.37	0.731	3.24
30	9.22	2.09	0.714	2.93
30	12.22	1.79	0.690	2.59
40	4.88	3.20	0.808	3.96
40	7.22	2.71	0.775	3.50
40	9.22	2.42	0.759	3.18
40	12.22	2.10	0.726	2.89

4.4.1 Relationship Analysis

Relationship analysis was conducted with pairwise correlation analyses between each of the finger trajectory measures and throughput, also between each pair of finger trajectory measures, as in prior work (MacKenzie et al., 2001). All correlation analyses were reported with the Pearson's correlation coefficient (r), along with the 2-tailed significant value with $p < .05$. The following scale was considered to determine the strength of correlations: strong ($r >= |0.50|$), moderate ($|0.30| <= r < |0.50|$), and weak ($r < |0.30|$) (Cohen, 1988).

The Pearson's correlation coefficient (r) between performance throughput (IP) and the finger trajectory measures are presented in Table 4.6. Among all finger trajectory measures, the following seven measures, direction changes along all axes (DC-X: $r = -0.62, p < .005$, DC-Y: $r = -0.58, p < .005$, DC-Z: $r = -0.64, p < .005$), pause frequency (PF: $r = -0.63, p < .005$), pause duration (PD: $r = -0.50, p < .005$), pause location distance (PLD: $r = -0.71, p < .005$), and path axis ratio (PAR: $r = -0.58, p < .005$) had significantly strong negative correlations with throughput. These results demonstrated that increased values in these seven measures can significantly decrease the performance throughput. Higher counts in direction changes along all axes (DC-X, DC-Y, DC-Z) indicate higher number of overshoots, undershoots, and corrective submovements during a selection task. Frequent long pauses (PF and PD) and higher values in pause location distance (PLD) indicate frequent submovements all over the trajectory. Higher path axis ratio (PAR) indicates higher deviation from the ideal selection path. Our results suggest that all of these selection behaviour can lead to generating low performance throughput in touch interaction. The remaining nine finger trajectory measures had weak to moderate, but not significant, correlations with throughput ($|0.04| <= r <= |0.31|, p > .05$ for all, see Table 4.6). However, four out of these nine remaining measures (i.e., task plane crossing (TPC), movement variability (MV), peak speed (SP), mean speed (SM)) had significantly strong correlations ($r >= |0.50|, p < .05$) with at least one of the measures that were strongly correlated to throughput (see Table 4.6). These strong correlations demonstrated that a majority of the new finger trajectory measures can directly or indirectly reflect on the low performance throughput of touch input.

To better understand the direct and indirect relationships between throughput and the finger trajectory measures, we construct a relationship model from the pairwise correlations that are reported in Table 4.6. We present the relationship model in Figure 4.14. The node that is colored in grey, represents the performance throughput (IP). The remaining nodes represent finger trajectory measures, and each connector represents a significantly strong correlation having $r >= |0.50|$ and $p < .05$. Nodes that are colored in blue, represent the measures having significantly strong correlations with throughput.

In this relationship model, we identified the following three distinct clusters where the inter-correlations between measures within the clusters were relatively strong, and the same for the outside of the clusters were relatively weak:

- **Cluster 1** consisted of all pause-related measures: pause frequency (PF), pause duration (PD), and pause location distance (PLD), all of which had significantly strong neg-

Table 4.6 Pairwise Pearson's correlations between throughput and all finger trajectory measures, for all participants ($** = p < .005$, $* = p < .05$.)

	IP	**DC-X**	**DC-Y**	**DC-Z**	**TPC**	**MV**	**MO**	**ME**	**PF**	**PD**	**PLD**	**PAR**	**SP**	**SM**	**RY**	**RP**
DC-X	-0.62**															
DC-Y	-0.58**	0.92**														
DC-Z	-0.64**	0.96**	0.87**													
TPC	-0.26	0.62**	0.51**	0.47**												
MV	-0.28	0.38*	0.08	0.49**	0.28											
MO	0.09	-0.09	0.02	-0.28	0.30	-0.68**										
ME	-0.10	0.05	-0.11.	0.23	-0.17	0.79**	-0.92**									
PF	-0.63**	0.11	0.14	0.11	-0.10	-0.09	0.07	-0.07								
PD	-0.50**	-0.04	-0.01	-0.04	-0.20	-0.14	0.12	-0.12	0.93**							
PLD	-0.71**	0.25	0.29	0.23	0.15	-0.07	0.18	-0.16	0.92**	0.86**						
PAR	-0.58**	0.91**	0.74**	0.94**	0.56**	0.62**	-0.26	0.23	0.06	-0.03	0.19					
SP	-0.31	0.83**	0.78**	0.82**	0.55**	0.31	-0.11	0.04	-0.09	-0.16	0.05	0.82**				
SM	0.04	0.65**	0.49**	0.64**	0.54**	0.47**	-0.17	0.10	-0.40*	-0.40*	-0.28	0.76**	0.83**			
RY	-0.13	-0.02	0.17	-0.03	-0.07	-0.32	-0.01	-0.07	0.14	0.04	0.11	-0.13	0.00	-0.26		
RP	-0.17	0.37*	0.26	0.42*	0.38*	0.67**	-0.50**	0.49**	-0.21	-0.31	-0.17	0.48**	0.27	0.43*	-0.14	
RR	0.18	-0.28	-0.06	-0.35*	-0.22	-0.81**	0.56**	-0.63**	0.19	0.18	0.15	-0.44*	-0.10	-0.35*	0.51**	-0.72**

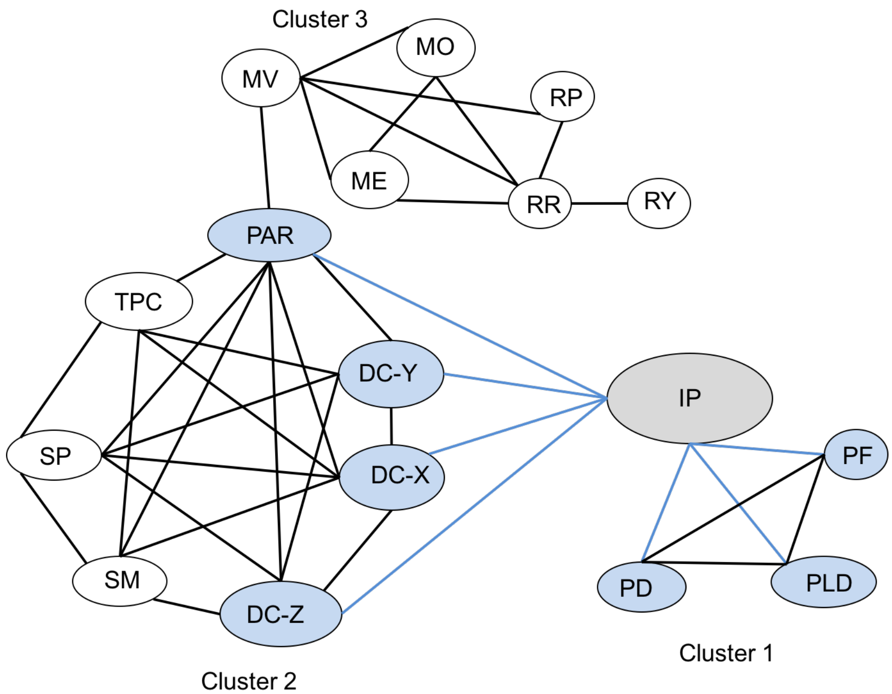


Figure 4.14 Relationship model for performance throughput (IP) and all finger trajectory measures. The shaded node represents IP, and other nodes represent finger trajectory measures. Trajectory measures having strong and significant correlations with throughput are colored in blue. All connectors represent a significantly strong correlation where $r > |0.50|$ and $p < .05$.

ative correlations with performance throughput ($-0.71 <= r <= -0.50, p < .005$ for all), and very strong and significant positive correlations among themselves ($0.86 <= r <= 0.93, p < .005$ for all). The pause related measures had mostly weak and non-significant correlations with other finger trajectory measures (see Table 4.6), except for mean speed (SM), which had moderate correlations (not shown in Figure 4.14) with PF ($r = -0.40, p < .05$) and PD ($r = -0.40, p < .05$). Higher values in pause measures suggest higher number of smaller submovements along the trajectories.

- **Cluster 2** consisted of the following seven measures: direction changes along all axes

(DC-X, DC-Y, and DC-Z), path axis ratio (PAR), task plane crossing (TPC), peak speed (SP) and mean speed (SM). Among them, only four measures: DC-X, DC-Y, DC-Z, and PAR had significantly negative strong correlations with performance throughput ($-0.64 <= r <= -0.58, p < .005$ for all). However, all of these four measures had significantly strong positive inter-correlations ($0.51 <= r <= 0.83, p < .005$ for all) with the remaining three measures (i.e., SP, SM, and TPC) within the cluster (see Table 4.6). The only significant moderate correlations observed within this cluster were between DC-Y and SM ($r = 0.49, p < .01$), and DC-Z and TPC ($r = 0.47, p < .01$) that are not shown in Figure 4.14. No weak or statistically non-significant inter-correlations were observed in this cluster. Higher direction changes along all axes, task plane crossing, and path axis ratio suggest higher counts of overshoots and undershoots, higher movement deviation from the ideal path, and higher counts in smaller sub-movements. Higher peak and mean speed suggest erratic movement that can cause higher deviation, and over and undershoot.

- **Cluster 3** consisted of the remaining six measures: movement variability (MV), movement offset (MO), movement error (ME), and rotations (mean pitch (RP), mean roll (RR), and mean yaw (RY)). None of these measures had strong, nor significant, correlations with throughput ($|0.09| <= r <= |0.28|, p > .05$ for all). However, like other clusters, the inter-correlations within this cluster were strong and significant ($|0.50| <= r <= |0.92|, p < .01$), except for RY, which was strongly correlated only to RR ($r = 0.51, p < .01$). Almost all of the measures from Cluster 3 had weak to moderate, but non-significant ($|0.08| <= r <= |0.49|, p > .05$) correlations outside the cluster. The only strong significant correlation outside the cluster was observed between MV and PAR (from Cluster 2) with $r = 0.62$ and $p < .01$. Recall that PAR was also strongly correlated to throughput. Higher movement variability, offset, error suggest higher deviation from the ideal path, possibly because of higher mean finger pitch, roll, and yaw.

The cluster structure of the relationship model (Figure 4.14) indicates strong interdependencies among the finger trajectory measures within the clusters. The relationships with throughput that we identified in this section, plausibly reflect the combined association between the measures from a cluster and throughput, rather than their individual association with throughput (MacKenzie et al., 2001). We present the dependency analysis in the next section to identify the independent contributions of each finger trajectory measures to throughput.

4.4.2 Dependency Analysis

In our dependency analysis, we followed prior work (MacKenzie et al., 2001) and conducted a series of multiple regression analysis. To determine the individual contributions of each finger trajectory measures to throughput, we generated prediction models from the regression analysis, where, all trajectory measures were included as independent variables and throughput as dependent variable. Similar to prior work (MacKenzie et al., 2001), we applied the forward selection method that added the independent variables having the highest common variance with dependent variable, in each step of model creation. Independent variables were included in the model, only if their common variance with the dependent variable was significant ($p < .05$). Common variances for regression analyses were reported with the coefficient of determination (r^2). We considered $r^2 >= 0.20$ as strong, $0.10 <= r^2 < 0.20$ as moderate, and $r^2 < 0.10$ as weak variance (Tabachnick & Fidell, 2001). The F-statistics and the p values of the final model were also reported.

Our multiple regression model for throughput is presented in the first row of Table 4.7. Two finger trajectory measures: pause location distance (PLD: $r^2 = 0.50$) and direction changes along the z-axis (DC-Z: $r^2 = 0.24$) made significantly strong independent contributions to throughput (final model: $r^2 = 0.90, F_{4,27} = 62.93, p < .0005$). These two measures together explained 74% of the variance with throughput. Higher values in pause location distance (PLD) indicate taking a number of smaller submovements throughout the selection trajectory, and higher counts in direction changes along the z-axis (DC-Z) indicate higher deviation from the ideal performance, and higher counts of submovements. Significantly strong common variance between these measures and throughput suggests that higher counts in smaller corrective submovements throughout the trajectory, due to overshoots and undershoots, significantly contribute on lower performance throughput in touch input. The remaining 16% independent contributions to throughput came from mean speed (SM: $r^2 = 0.09$) and path axis ratio (PAR: $r^2 = 0.07$). However, those independent contributions were weak. Recall that our relationship analysis in Section 4.4.1 determined significantly strong negative correlations between throughput and the following seven finger trajectory measures: pause frequency, location, and distance (PF, PD, PLD), direction changes along all axes (DC-X, DC-Y, DC-Z), and path axis ratio (PAR). Our dependency analysis demonstrated that among these seven measures, only two of them, namely pause location distance (PLD) and direction changes along the z-axis (DC-Z), had significantly strong independent contributions to throughput. The remaining measures had significantly strong correlations with throughput possibly because of their strong correlations with PLD and DC-Z (see Figure 4.14), but not because of their independent contributions to throughput. We will elaborate on this later when we present the dependency analysis among the trajectory measures.

To determine the interdependencies among the finger trajectory measures, we conducted subsequent rounds of multiple regression analyses on these measures, as shown in prior work (MacKenzie et al., 2001). In each round, the most significant independent variable with the highest independent contribution, identified in the previous round, was treated as the dependent variable, and the remaining measures were included as independent ones. For example, in the first round, we considered pause location distance (PLD) as the dependent variable of the regression analysis, as it had the highest common variance with throughput (see Table 4.7). The remaining finger trajectory measures were treated as independent variables. This process continued until we exhausted all such dependencies (i.e., no remaining independent variables had significant ($p < .05$) common variance with the dependent variable), or the common variances between a dependent variable and all independent variables were weak to moderate ($r^2 < 0.20$). Results from the regression analyses among the finger

Table 4.7 Results from multiple regression analyses between performance throughput and the finger trajectory measures.

Dependent Variable	**Independent Variable(s) (r^2)**	**Final Model**
IP	PLD (0.50), DC-Z (0.24), SM (0.09), PAR (0.07)	$r^2 = 0.90, F_{4,27} = 62.93, p < .0005$
PLD	PF (0.84), TPC (0.06)	$r^2 = 0.90, F_{2,29} = 126.44, p < .0005$
PF	PD (0.86), DC-X (0.02), SM (0.03)	$r^2 = 0.91, F_{3,28} = 103.02, p < .0005$
PD	SM (0.16), PAR (0.17)	$r^2 = 0.33, F_{2,29} = 7.23, p < .005$
DC-Z	DC-X (0.93), MO (0.04), PAR (0.01), TPC (0.01)	$r^2 = 0.99, F_{4,27} = 314.21, p < .0005$
DC-X	DC-Y (0.85), PAR (0.11)	$r^2 = 0.96, F_{2,29} = 371.52, p < .0005$
DC-Y	SP (0.60), SM (0.07), PAR (0.07), MV (0.09), RP (0.05), RR (0.02), PD (0.01), PF (0.01)	$r^2 = 0.92, F_{8,23} = 44.87, p < .0005$
SP	SM (0.68), PLD (0.09), RY (0.04)	$r^2 = 0.81, F_{3,28} = 39.12, p < .0005$
SM	PAR (0.58)	$r^2 = 0.58, F_{1,30} = 41.12, p < .0005$
PAR	MV (0.39), ME (0.18)	$r^2 = 0.57, F_{2,29} = 18.81, p < .0005$
MV	RR (0.65), ME (0.13), TPC (0.08)	$r^2 = 0.86, F_{3,28} = 55.40, p < .0005$
RR	RP (0.52), RY (0.17), ME (0.10)	$r^2 = 0.79, F_{3,28} = 34.56, p < .0005$
RP	TPC (0.31), MO (0.25)	$r^2 = 0.56, F_{2,29} = 18.00, p < .0005$
TPC	None	
MO	ME (0.84)	$r^2 = 0.84, F_{1,30} = 154.96, p < .0005$
ME	None	

trajectory measures are also reported in Table 4.7. Each row of this table represents the final multiple regression model after adding all qualifying independent variables, applying the forward selection method. For each multiple regression analysis, we report all dependent and independent variables that were included in the final model. Independent variables are reported with their common variances with the dependent variable. The r^2 values, along with the F-statistics of the final regression models are also reported.

As we explore the two strongest independent contributors to throughput (i.e., pause location distance (PLD) and direction changes along the z-axis (DC-Z)), we observed strong interdependencies among PLD and DC-Z with four out of the five measures (i.e., PF, PD, DC-X, and DC-Y) that had strong negative correlations with throughput (see Tables 4.6 and 4.7). Pause location distance (PLD) had strong contributions from pause frequency (84% common variance with PLD), and pause duration (86% common variance with PF). Direction changes along the z-axis (DC-Z) had strong contributions from direction changes along x-axis (93% common variance with DC-Z), and direction changes along y-axis (85% common variance with DC-X). Although path axis ratio (PAR) had strong correlations with throughput ($r = -0.58, p < .005$) and direction changes along z-axis ($r = 0.94, p < .005$), it did not have strong independent contributions to either of them.

We constructed a dependency model (see Figure 4.15) between throughput and the finger trajectory measures from our dependency analysis. The node representing performance throughput (IP) is colored in grey. The remaining nodes represent the finger trajectory measures. Nodes are connected if they share moderate to strong common variance. Connectors are labeled with r^2 values, where, solid connectors represent a strong common variance ($r^2 >= 0.20$) and dashed connectors represent a moderate one ($0.10 <= r^2 < 0.20$). Nodes that have strong common variance with throughput are colored in blue.

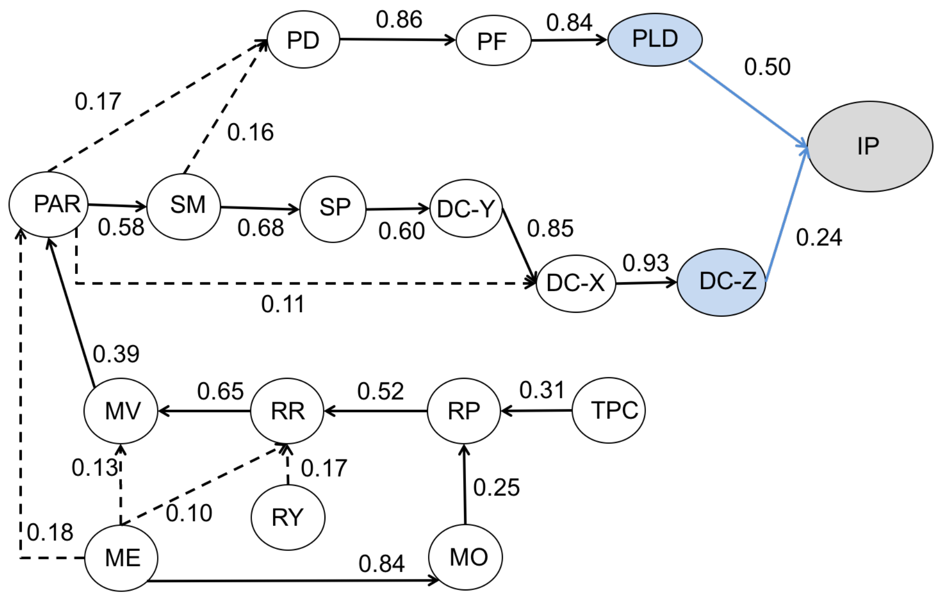


Figure 4.15 Dependency model between performance throughput and finger trajectory analysis measures. The solid lines represent strong ($r^2 >= 0.20$), and the dashed lines represent moderate ($0.10 <= r^2 < 0.20$) contributions. Weak contributions ($r^2 < 0.10$) are not shown in the model.

The dependency model mostly conforms to the cluster structure of the relationship model that was presented in Figure 4.14. The dependency branch led by pause location distance (PLD) had major contributions from the other pause-related measures: pause frequency (PF) and pause duration (PD), both from Cluster 1 of the relationship model (see Figure 4.14). Pause duration (PD) had combined 33% common variance from PAR ($r^2 = 0.17$) and SM ($r^2 = 0.16$), both were from Cluster 2 of the relationship model, where, SM had moderate correlation with PD ($r = -0.40, p < .05$). The dependency branch led by direction changes along the z-axis (DC-Z) had major contributions from direction changes along the x-axis (DC-X), direction changes along the y-axis (DC-Y), peak speed (SP), mean speed (SM), and path axis ratio (PAR), all of them belonged to Cluster 2 of the relationship model (see Figure 4.14). We also observed that two measures: movement variability (MV: $r^2 = 0.39$) and movement error (ME: $r^2 = 0.18$), both from the Cluster 3 of the relationship model, contributed in total 57% of common variance for path axis ratio (PAR). In the relationship model, MV had strong correlation with PAR ($r = 0.62, p < .005$). Movement variability (MV) had moderate to strong dependencies with the other measures: movement error (ME), mean roll (RR), mean pitch (RP), mean yaw (RY), and movement offset (MO) from Cluster 3 of the relationship model (see Figure 4.14). The only exception was task plane crossing (TPC) that belonged to Cluster 2 of the relationship model, but had 31% common variance with mean pitch (RP) from Cluster 3, but had no strong dependency with any measures from Cluster 2 of the relationship model.

Findings from both relationship and dependency analyses made it clear that higher values in a subset of the finger trajectory measures can indicate lower performance throughput in touch input. Having longer selection trajectories, frequently pausing and changing directions throughout the trajectories were strongly associated with low performance throughput. Higher values in these measures suggest that individuals were prone to overshoots, undershoots, and deviation from the task axis. They generated smaller corrective submovements throughout the trajectory to select the target. These selection difficulties with touch input eventually affected their performance throughput.

4.5 Summary

In this chapter, we introduce sixteen three-dimensional finger trajectory measures, and analyzed their reliability to understand low performance throughput with touch input. As a secondary contribution, we present a custom-built finger trajectory data collection tool that can capture mid-air trajectory data from touch interaction. The study presented in this chapter demonstrated that the finger trajectory measures can provide more in-depth insight on low performance throughput in touch input. These measures can indicate selection difficulties that are encountered throughout the selection trajectories, in addition to reporting error rates that reflect on difficulties at the selection endpoints. The relationship and dependency analyses presented in this chapter included selection task data from both older and younger adults, and provided a general view on the associations between throughput and the finger trajectory measures from a broader range of users. Findings from this study provided us the confidence that it is worth further investigating the differences in the finger trajectory measures across age groups, and how do these differences impact the overall performance throughput of older adults. In the next chapter (Chapter 5), we present a study that analyzes the finger trajectory measures across age groups to answer these questions.

Chapter 5

Finger Trajectory Analysis

5.1 Introduction and Motivation

Chapter 4 laid the groundwork for understanding the age-related differences observed in the finger trajectories from touch input. We first extended the existing two-dimensional cursor trajectory measures that were developed for mouse input (Hwang et al., 2005; Keates & Trewin, 2005; MacKenzie et al., 2001), to three-dimensional finger trajectory measures to be applied on touch input. Then, we demonstrated that higher values in a subset of these measures are strongly associated with lower performance throughput. Moreover, we observed three clusters of finger trajectory measures with strong interdependencies within those clusters. In Section 5.3.2, we investigate which of these finger trajectory measures demonstrate performance differences between older and younger adults. Next, in Section 5.3.3 we investigate how these finger trajectory measures influence the age-related performance differences in throughput of touch input. In particular, we answer the following research question (*RQ3*) of this thesis:

> *RQ3.1: How can the finger trajectory analysis measures be used to characterize age-related performance differences?*
>
> *RQ3.2: How does age influence the relationships and dependencies between the finger trajectory analysis measures and performance throughput?*

The trajectory analysis study presented in this chapter used the same dataset from Chapter 4 to answer *RQ3.1* and *RQ3.2*. To decode the age-related performance differences in finger trajectory measures (*RQ3.1*), we examined if older adults had disproportionately higher values in any of these measures, compared to younger adults. We also analyzed age-related performance differences in the finger trajectory measures, across different target widths, amplitudes and locations. To understand the influence of age on the relationships and dependencies between the finger trajectory measures and performance throughput (*RQ3.2*), we conducted relationship and dependency analyses between these measures and throughput in individual age groups, similar to the relationship and dependency analyses, presented in Chapter 4, for combined age groups.

Our study results demonstrated that age-related performance differences were evident in direction change counts along all axes, movement variability, path axis ratio, pause location distance, peak speed, and finger rolling, where older adults had significantly higher values in each of these measures. These results imply that older adults had higher deviation from the task axis, encountered higher counts of overshoots and undershoots, and generated a number of smaller corrective submovements during target selection. Moreover, older adults had lower throughput than younger adults, across all target amplitude-width combinations. The relationship and dependency analyses in individual age groups separated the trajectory measures that affected the performance throughput of only older adults, from the measures that affected the throughput in both age groups. In particular, frequent long pauses were the reasons for lower throughput in both older and younger adults. However, the remaining trajectory measures had direct and indirect influence on low performance throughput in only older adults.

5.2 Method and Materials

As we mentioned before, we used the same dataset from Chapter 4 in this trajectory analysis study. Study data were collected from a two-dimensional Fitts's task-like selection task (Fitts, 1954; Ren & Moriya, 2000), from both older and younger adults, in a controlled lab environment. Younger adult participants were included to investigate the performance differences in the finger trajectory measures, across age groups. Both trajectory analysis study and error analysis study from Chapter 3 across age groups followed very similar methodologies. A comparison between the methodologies of these two studies are presented in Table 5.1. Details on the method and materials of this study can be found on Section 4.3 of Chapter 4.

Table 5.1 Comparisons between the error analysis study from Chapter 3 and the trajectory analysis study.

Properties	**Error Analysis Study**	**Trajectory Analysis Study**
Participants	Older Adults ($n = 20$ (14 F, 6 M); age: 67-81; mean(SD): 73.3(4.89)) Younger Adults ($n = 16$ (12 F, 4 M); age: 22-35, mean(SD): 28.9(3.73))	Older Adults ($n = 16$ (7 F, 9 M); age: 66-81; mean(SD): 73.4(4.23)) Younger Adults ($n = 16$ (9 F, 6 M, 1 Undisclosed); age: 20-34; mean(SD): 26.4(4.19))
Apparatus	Motorola Nexus 6 Smartphone (Screen Size: 74.19 × 131.89 mm)	HTC Nexus 9 Tablet (Screen Size: 135.47 × 180.62 mm), and a LEAP Motion Controller connected with a MacBook Pro Laptop (2.9 GHz, OS X 10.10.5)
Device Orientation	Held by the left hand, in a portrait orientation	Reclined at 45° angle on a table top, in a landscape orientation
Task	2-D Fitts's task-like selection task Finger Calibration Task (not reported)	2-D Fitts's task-like selection task
Target Amplitudes	20 mm, 30 mm	20 mm, 30 mm, 40 mm
Target Widths	4.88 mm, 7.22 mm, 9.22 mm	4.88 mm, 7.22 mm, 9.22 mm, 12.22 mm
Target Angles	0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°	0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°
Design	2 (age groups) × 4 (blocks) × 3 (widths) × 2 (amplitudes) × 8 (angles)	2 (age groups) × 4 (blocks) × 4 (widths) × 3 (amplitudes) × 8 (angles)

5.3 Results

In this section, we present our study results to answer *RQ3.1* and *RQ3.2*. In Section 5.3.1, we present an overall performance analysis of the selection task to ensure that our study data are consistent with the findings presented in the error analysis study from Chapter 3, as both studies applied very similar methodologies (see Table 5.1). The overall performance is presented in terms of movement time and error rates. In Section 5.3.2, we examine the age-related performance differences in the finger trajectory measures (*RQ3.1*). In Section 5.3.3, we investigate how ageing influences the relationships and dependencies between the finger trajectory measures and throughput (*RQ3.2*).

5.3.1 Overall Performance

Our study results demonstrated significant overall performance differences between older and younger adults. These results are consistent with the results from our error analysis study (Chapter 3) and prior works (Keates & Trewin, 2005; Moffatt & McGrenere, 2007). We applied descriptive and inferential statistical analyses in both Sections 5.3.1 and 5.3.2 to identify performance differences across age groups. Results from the descriptive statistics included group means and standard deviations (SD). As no participant's data were outliers (i.e., three standard deviations away from the group mean) in their respective age groups, we did not present any individual participant's data in these sections. The inferential statistics included a repeated measure ANOVA analysis of each measure, according to the study design

(2 age groups × 3 amplitudes × 4 widths × 8 angles), where, age is the only between-subject factor (see Section 4.3.4 for more details). Pairwise performance comparisons in the repeated measure ANOVAs were corrected with a Bonferroni correction. We also conducted Mauchly's test to identify sphericity violations, and corrected such violations with Greenhouse-Geisser corrections; where degrees of freedom (*df*) are non-integer, a correction has been applied. We also reported partial eta-squared (η_p^2), a measure of effect size. Throughout these sections, we emphasized on presenting the significant main and interaction effects of the factors. Full results of the descriptive and inferential statistical analyses are included in Appendix C.

Movement Time

Older adults had significantly higher movement times ($F_{1,29} = 39.86, p < .00001, \eta_p^2 = .58$) than younger adults (see Figure 5.1(left)). Moreover, in both age groups, movement times significantly increased as the target widths decreased ($F_{1.63,47.23} = 116.65, p < .00001, \eta_p^2 = .80$, see Figure 5.2(left)) and the target amplitude increased ($F_{1.47,42.54} = 285.84, p < .00001, \eta_p^2 = .91$, see Figure 5.2(right)). Main effect of target angle was also significant on movement time ($F_{3.95,114.57} = 13.21, p < .00001, \eta_p^2 = .31$, see Figure 5.3). We observed the right-hand occlusion effect that increased the movement times for selecting targets located at the right-hand corner of the screen (see Figure 5.3), as it was observed in prior work (Hancock & Booth, 2004), and in our study from Chapter 3. A small interaction effect of age × angle was observed on movement time ($F_{3.95,114.57} = 2.60, p < .05, \eta_p^2 = .08$, see Figure 5.4). Movement time for older adults were disproportionately higher than younger adults for the targets located at the bottom of the screen.

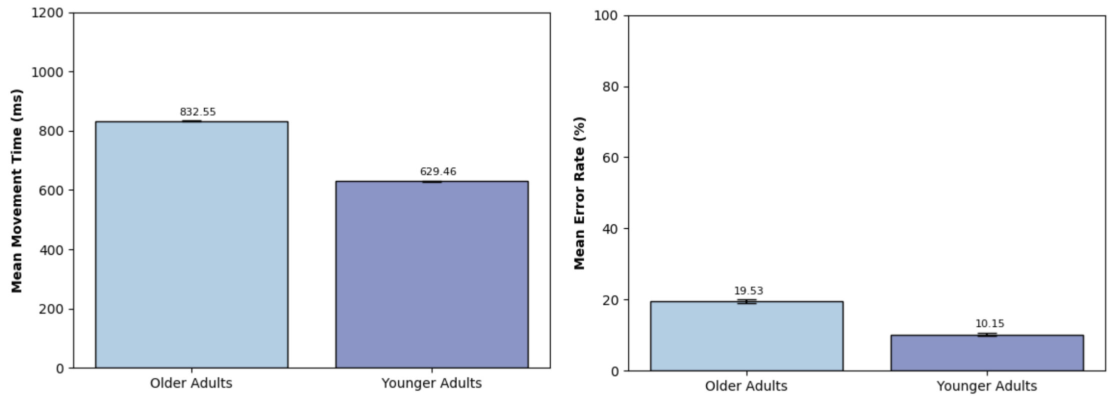


Figure 5.1 Performance differences in mean movement times (left) and error rates (right) by age group. For older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

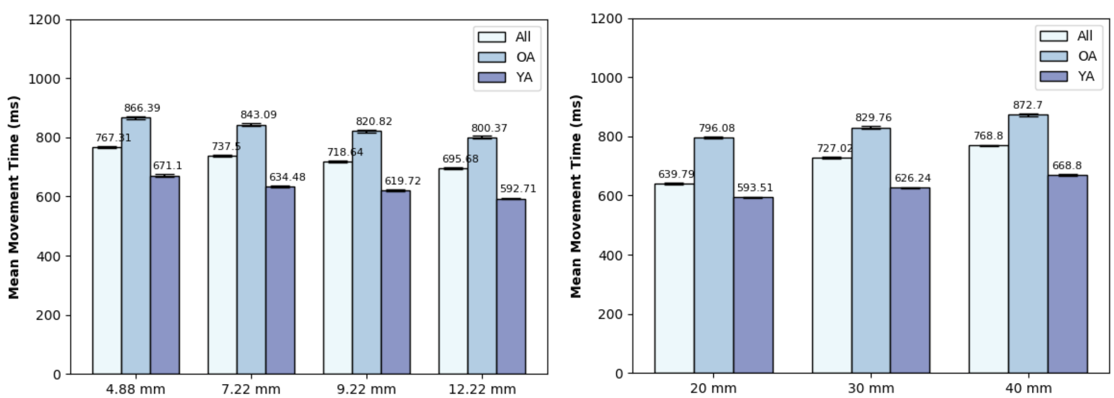


Figure 5.2 Mean movement times by target width (left) and target amplitudes (right). For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

Error Rate

Error rate was also significantly higher in older adults ($F_{1,29} = 10.61$, $p <.005$, $\eta_p^2 = .27$, see Figure 5.1(right)). Error rates significantly increased as target widths decreased in both age groups ($F_{1.45,42.09} = 164.97$, $p < .00001$, $\eta_p^2 = .85$, see Figure 5.5). A strong interaction effect

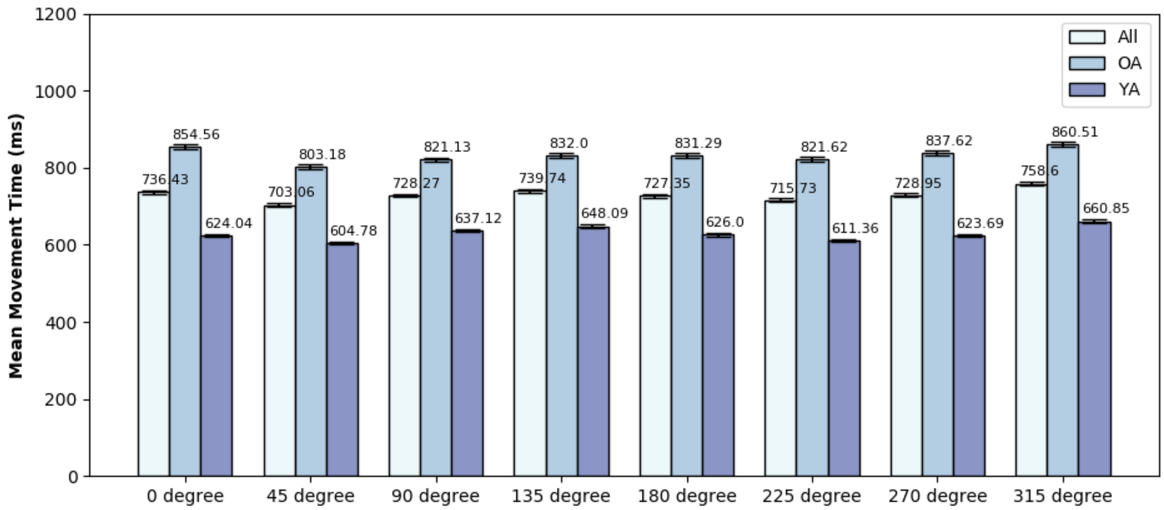


Figure 5.3 Mean movement times by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

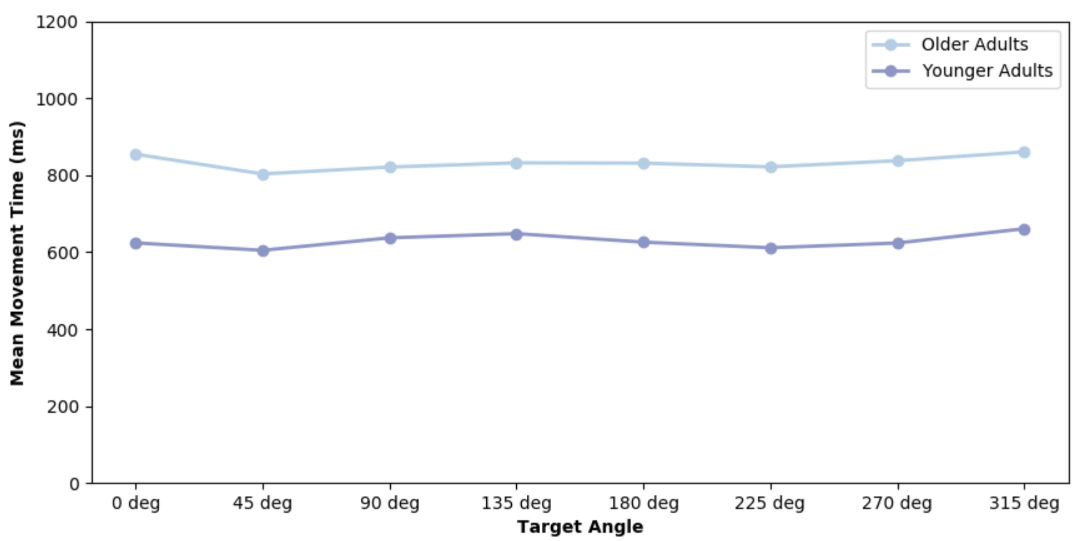


Figure 5.4 Interaction effect of age $\times$ angle on mean movement time. For both older and younger adults, $n = 16$.

of age × width was observed ($F_{1.45,42.09} = 11.77$, $p < .0005$, $\eta_p^2 = .29$, see Figure 5.6). Older adults disproportionately generated more errors with smaller targets, compared to younger adults. No main effect of amplitudes ($p = .258$) and angles ($p = .731$) were observed on error rates.

Both in this trajectory analysis study and the error analysis study (presented in Chapter 3), we reported high error rates among older adults with the targets comparable in size to those of selectable items on popular smartphones and tablets (i.e., between 4.88 mm to 9.22 mm). For older adults, in the error analysis study the error rate was between 9.74% and 62.40%, and in the trajectory analysis study the error rate was between 9.11% and 44.82%. Both studies also reported that performance gaps between older and younger adults reduced as we increased the target widths. In this study, we extended existing knowledge on the relationship between target size and accessibility for older adults, by extending the target size to 12.22 mm in width. Increasing the targets by 33% (i.e., from a standard icon size of 9.22 mm to 12.22 mm) reduced the error rates into more than half in both older and younger adults (older adults: 9.22 mm (9.11%) vs. 12.22 mm (4.07%); younger adults: 9.22 mm (4.18%) vs. 12.22 mm (1.71%)). Moreover, as the target size increased up to 12.22 mm, error rates in older adults decreased to 4.07%, which is also very close to the 4% threshold, commonly deemed acceptable for pointing performance (MacKenzie, 1992). Not only that, the pairwise performance difference between older and younger adults at 12.22 mm targets became non-significant ($p > .05$). Our results emphasize the need for an ability to increase the size of selectable items on touchscreen interfaces to at least 12.22 mm in order to support the accessibility requirements of older adults.

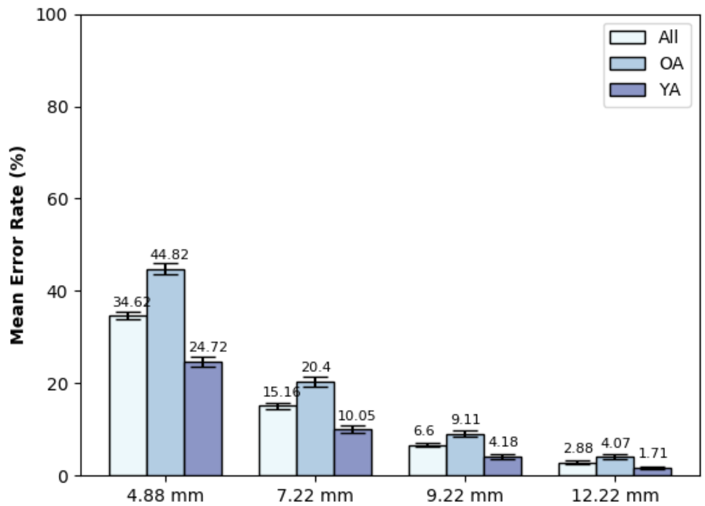


Figure 5.5 Mean error rates by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

Subjective Analysis

Responses of both older and younger adults from the post experiment questionnaire matched the results from overall performance. These responses also strongly aligned with the responses from the error analysis study. Older adults generally preferred the larger targets (9.22 mm and 12.22 mm) to achieve better speed and accuracy. Participants from both age groups mentioned that targets located at the lower-right quadrant were the most difficult and least preferred to select, especially when the targets were small (4.88 mm).

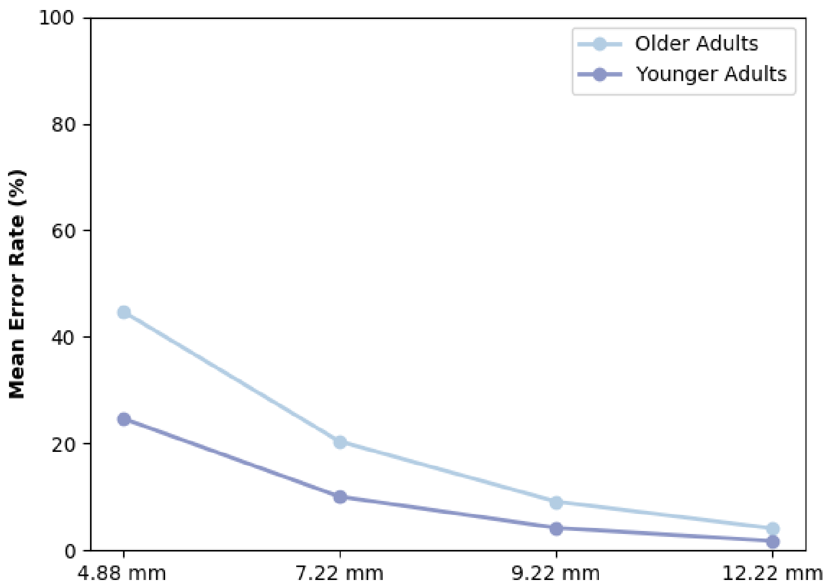


Figure 5.6 Mean error rate at each target width for older adults ($n = 16$) and younger adults ($n = 16$). While older adults made significantly more errors than younger adults for all target widths, the error rate disproportionately increases for older adults as target size decreases.

5.3.2 Age-related Differences in the Finger Trajectory Measures

Results from our descriptive and inferential statistical analyses on finger trajectory measures across age groups are reported in Table 5.2. Details on the descriptive and inferential statistical analyses applied in this section can be found in Section 5.3.1. Higher mean absolute values in all finger trajectory measures were observed in older adults, compared to younger adults. We also observed high performance variability in older adults. Significant statistical differences across age groups were evident for the following eight measures: direction changes along all axes (DC-X, DC-Y, and DC-Z), movement variability (MV), path axis ratio (PAR), pause location distance (PLD), peak speed (SP), and mean roll (RR). In the following subsections we present the results from our ANOVA analysis on these eight finger trajectory measures, followed by a summary of these analyses (see page 165 for the summary). Complete ANOVA analysis results of all finger trajectory measures are reported in Appendix C.

Table 5.2 Mean and SD values of all finger trajectory measures across age groups.

Trajectory Measures	Older Adults Mean (SD)	Younger Adults Mean (SD)	F(1, 28)	η_p^2
DC-X	4.39 (2.92)	3.01 (2.02)	20.73**	0.43
DC-Y	5.62 (3.99)	3.83 (2.66)	12.00**	0.30
DC-Z	4.98 (3.67)	3.00 (2.44)	30.21**	0.52
TPC	0.46 (0.72)	0.42 (0.59)	*n.s.*	
MV	10.59 (10.14)	7.70 (7.77)	6.57*	0.19
ME	20.84 (12.66)	17.87 (10.45)	*n.s..*	
MO	-14.50 (15.34)	-12.53 (13.35)	*n.s.*	
PAR	3.24 (2.11)	1.96 (1.47)	29.40**	0.51
PF	0.21 (0.89)	0.11 (0.47)	*n.s.*	
PD	2.08 (7.46)	1.31 (5.14)	*n.s.*	
PLD	15.06 (43.79)	10.04 (35.10)	4.26*	0.13
SP	379.70 (331.9)	293.50 (271.6)	7.71*	0.22
SM	125.66 (54.94)	113.67 (53.40)	*n.s.*	
RY	-14.53 (34.53)	-13.77 (35.52)	*n.s.*	
RP	-24.50 (35.49)	-31.49 (30.52)	*n.s.*	
RR	-39.93 (50.97)	-24.17 (32.62)	6.00*	0.18

*** = p < .005, * = p < .05, n.s. = not significant*

Direction Changes Along X-axis (DC-X)

Older adults had significantly more direction changes along x-axis (DC-X) than younger adults ($F_{1,28} = 20.73, p < .0001, \eta_p^2 = .43$, see Figure 5.7). Moreover, the differences in number of DC-X between the older and the younger adults were significant across all target widths, amplitudes, and angles (see Table 5.3).

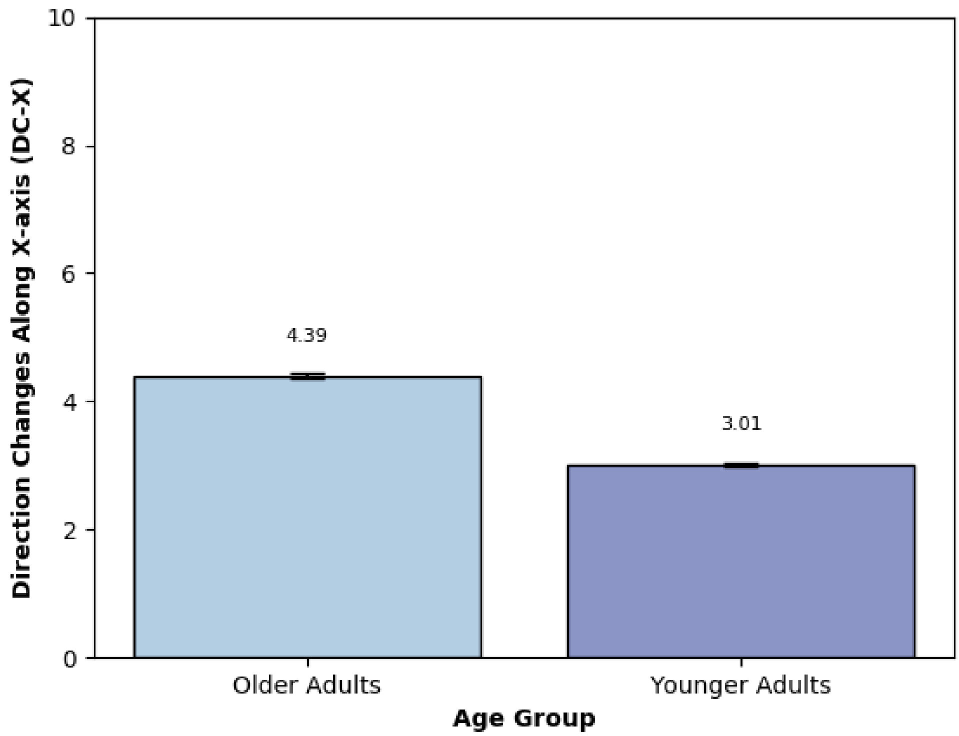


Figure 5.7 Mean direction changes along x-axis (DC-X) across age groups. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

Main effects of target widths on DC-X were observed for all participants ($F_{3,84} = 3.61, p < .05, \eta_p^2 = .11$, see Figure 5.8). However, in individual age groups, no such main effects were evident (older adults: $p = .062$, younger adults: $p = .544$). Our pairwise analysis reported performance differences only between the 4.88 mm–12.22 mm ($p < .01$), and the 7.22 mm–12.22 mm ($p < .05$) width pairs in older adults.

We observed significant main effect of target amplitude on DC-X for all participants ($F_{1.60,44.65} = 7.39, p < .005, \eta_p^2 = .21$, see Figure 5.9), and for older adults ($F_{2,27} = 5.29, p < .05, \eta_p^2 = .28$), but not for the younger adults (p = .091). The pairwise differences across all amplitudes were significant only for the 20 mm–40 mm amplitude pairs (all participants:

Table 5.3 Age-related performance differences in direction changes along x-axis (DC-X) across target width, amplitude, and angle.

Width (mm)	4.88	$F_{1,28} = 23.26$	$p < .00005$	$\eta_p^2 = .45$
	7.22	$F_{1,28} = 17.77$	$p < .0005$	$\eta_p^2 = .39$
	9.22	$F_{1,28} = 19.43$	$p < .0005$	$\eta_p^2 = .41$
	12.22	$F_{1,28} = 16.76$	$p < .0005$	$\eta_p^2 = .37$
Amplitude (mm)	20	$F_{1,28} = 19.23$	$p < .0005$	$\eta_p^2 = .41$
	30	$F_{1,28} = 18.97$	$p < .0005$	$\eta_p^2 = .41$
	40	$F_{1,28} = 20.67$	$p < .0001$	$\eta_p^2 = .43$
Angle (degree)	0	$F_{1,28} = 32.21$	$p < .00001$	$\eta_p^2 = .54$
	45	$F_{1,28} = 9.88$	$p < .005$	$\eta_p^2 = .26$
	90	$F_{1,28} = 6.32$	$p < .05$	$\eta_p^2 = .18$
	135	$F_{1,28} = 8.06$	$p < .01$	$\eta_p^2 = .22$
	180	$F_{1,28} = 11.21$	$p < .005$	$\eta_p^2 = .29$
	225	$F_{1,28} = 13.85$	$p < .001$	$\eta_p^2 = .33$
	270	$F_{1,28} = 22.52$	$p < .0001$	$\eta_p^2 = .45$
	315	$F_{1,28} = 37.75$	$p < .00001$	$\eta_p^2 = .57$

$p < .005$, older adult: $p < .01$, younger adults: $p < .05$).

Main effects of target angles were observed on DC-X for all participants ($F_{4.90,137.06} = 23.87, p < .00001, \eta_p^2 = .46$, see Figure 5.10), older adults ($F_{7,22} = 5.91, p < .001, \eta_p^2 = .64$), and younger adults ($F_{7,22} = 16.13, p < .00001, \eta_p^2 = .84$). Moreover, the interaction effect of age × angle on ($F_{4.90,137.06} = 5.59, p < .00001, \eta_p^2 = .17$, see Figure 5.11) showed that older adults had disproportionately more DC-X than younger adults for the targets located at the bottom-right quadrant (0°, 270°, and 315°) of the screen.

Direction Changes Along Y-Axis (DC-Y)

Older adults had significantly more direction changes along the y-axis (DC-Y) than younger adults ($F_{1,28} = 12.00, p < .005, \eta_p^2 = .30$, see Figure 5.12). Significant age-related perfor-

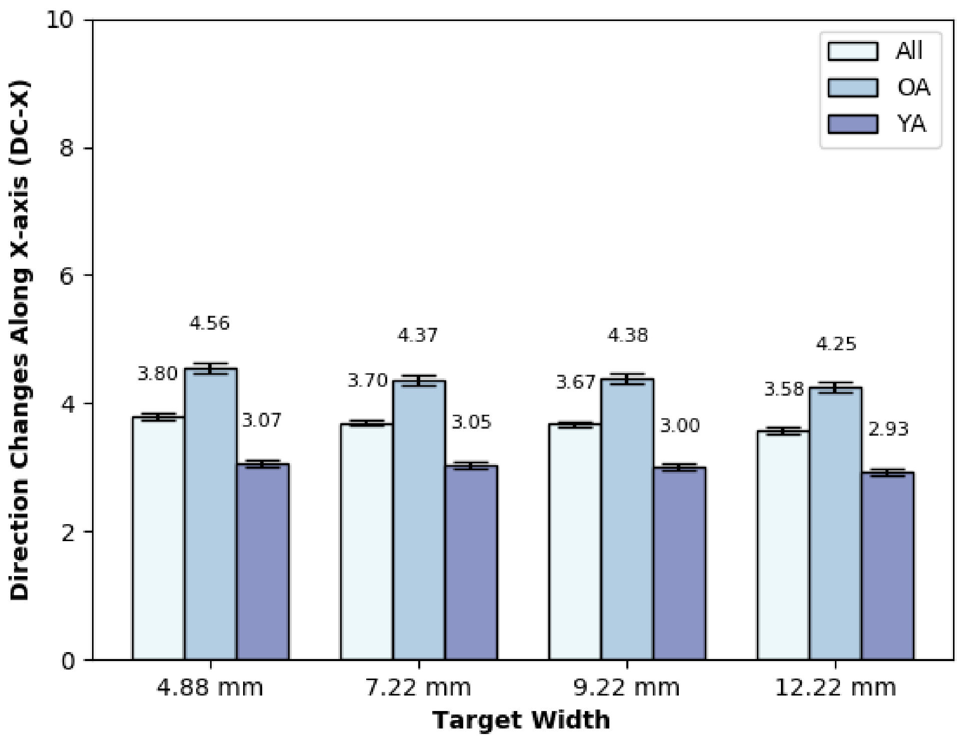


Figure 5.8 Mean direction changes along x-axis (DC-X) by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

mance differences between older and younger adults were evident across all target widths, amplitudes, and angles (see Table 5.4).

Target width had main effect on DC-Y ($F_{3,84} = 5.72, p < .005, \eta_p^2 = .17$, see Figure 5.13). However, in individual age groups, such main effect was only evident for the older adults ($F_{3,26} = 3.57, p < .05, \eta_p^2 = .29$), but not for the younger adults ($p = .266$). The pairwise performance difference analysis across target widths reveled significant differences only for the following width pairs in older adults: 4.88 mm–12.22 mm ($p < .005$), and 7.22 mm–12.22 mm ($p < .05$).

Target amplitude had significant main effect on DC-Y (all participants: $F_{2,56} = 68.35, p <$

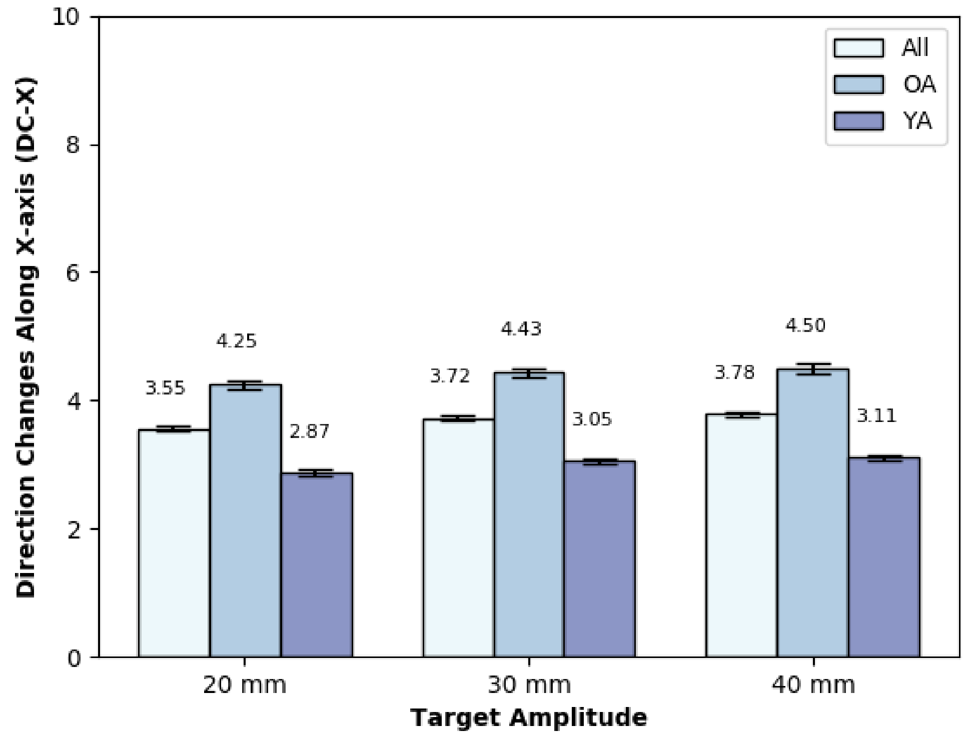


Figure 5.9 Mean direction changes along x-axis (DC-X) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

$.00001, \eta_p^2 = .71$, older adults: $F_{2,27} = 31.42, p < .00001, \eta_p^2 = .70$, and younger adults: $F_{2,27} = 22.87, p < .00001, \eta_p^2 = .63$, see Figure 5.14). Pairwise analysis across target amplitudes showed significant differences in DC-Y in all amplitude pairs (all participants: $p < .00001$, older adult: $p < .005$, younger adults: $p < .0005$).

Main effects of target angles were observed on DC-Y for all participants ($F_{4.48,125.56} = 39.24, p < .00001, \eta_p^2 = .58$), older adults ($F_{7,22} = 9.53, p < .00005, \eta_p^2 = .75$), and younger adults ($F_{7,22} = 13.93, p < .00001, \eta_p^2 = .82$, see Figure 5.15). For both older and younger adults, targets located at the left side of the screen (135°, 180° and 225°) had more DC-

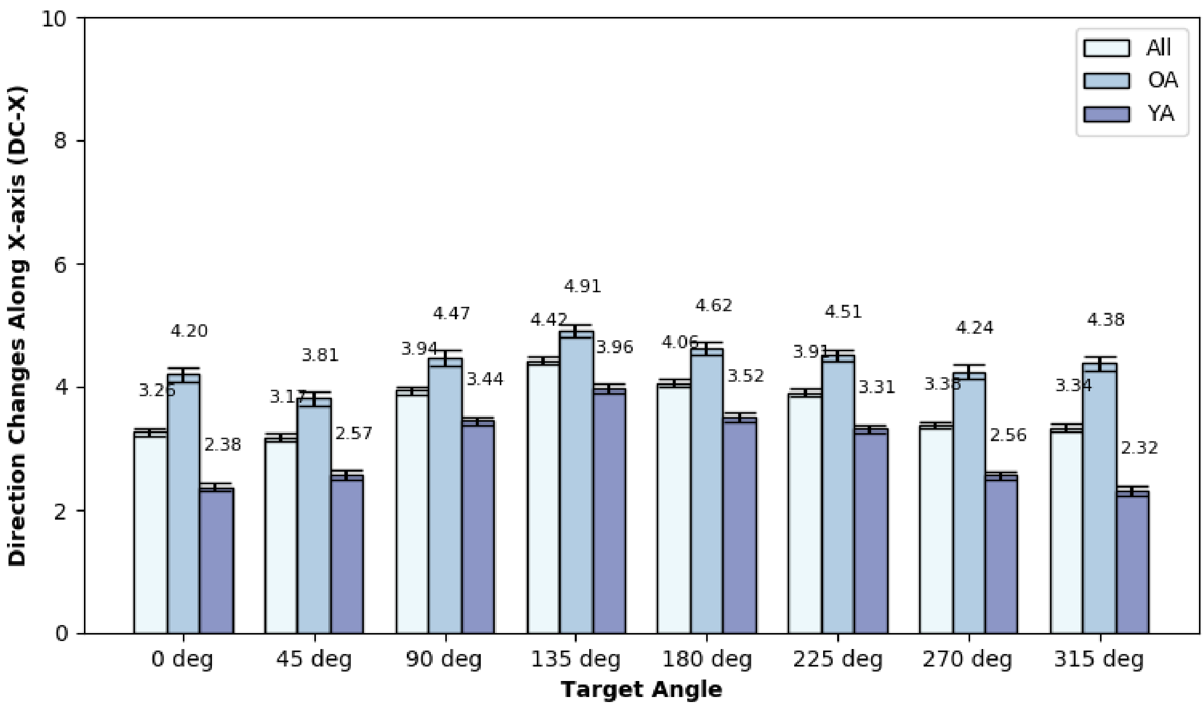


Figure 5.10 Mean direction changes along x-axis (DC-X) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Y than targets located the right side of the screen. The interaction effect of age × angle on DC-Y ($F_{4.48,125.56} = 4.15, p < .005, \eta_p^2 = .13$, see Figure 5.16) revealed that older adults encountered disproportionately higher number of DC-Y than younger adults with the targets located at the bottom of the screen (i.e., 225°, 270°, and 315°).

Direction Changes Along Z-axis (DC-Z)

We observed significant age-related performance differences in movement direction change along the z-axis (DC-Z) per trial ($F_{1,28} = 30.21, p < .00001, \eta_p^2 = .52$, see Figure 5.17). The age-related performance differences were also significant across all target widths, amplitudes,

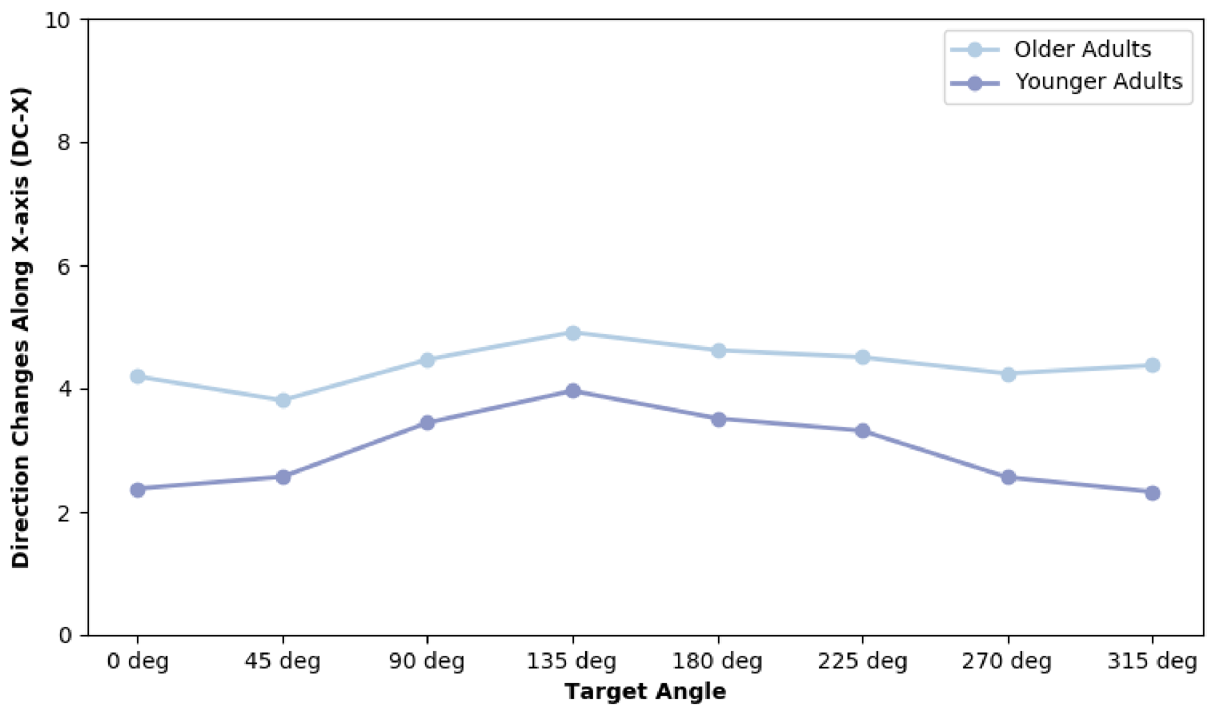


Figure 5.11 Interaction effect of age × angle on direction changes along x-axis (DC-X). For both older and younger adults ($n = 16$).

Table 5.4 Age-related performance differences in direction changes along y-axis (DC-Y) between older and younger adults.

Width (mm)	4.88	$F_{1,28} = 11.44$	$p < .005$	$\eta_p^2 = .29$
	7.22	$F_{1,28} = 10.65$	$p < .005$	$\eta_p^2 = .28$
	9.22	$F_{1,28} = 12.68$	$p < .005$	$\eta_p^2 = .31$
	12.22	$F_{1,28} = 11.47$	$p < .005$	$\eta_p^2 = .29$
Amplitude (mm)	20	$F_{1,28} = 11.96$	$p < .005$	$\eta_p^2 = .30$
	30	$F_{1,28} = 10.37$	$p < .005$	$\eta_p^2 = .27$
	40	$F_{1,28} = 12.71$	$p < .005$	$\eta_p^2 = .31$
Angle (degree)	0	$F_{1,28} = 12.67$	$p < .005$	$\eta_p^2 = .31$
	45	$F_{1,28} = 5.89$	$p < .05$	$\eta_p^2 = .17$
	90	$F_{1,28} = 6.32$	$p < .05$	$\eta_p^2 = .18$
	135	$F_{1,28} = 4.39$	$p < .05$	$\eta_p^2 = .14$
	180	$F_{1,28} = 9.67$	$p < .005$	$\eta_p^2 = .26$
	225	$F_{1,28} = 11.08$	$p < .005$	$\eta_p^2 = .28$
	270	$F_{1,28} = 21.30$	$p < .0001$	$\eta_p^2 = .43$
	315	$F_{1,28} = 18.95$	$p < .0005$	$\eta_p^2 = .40$

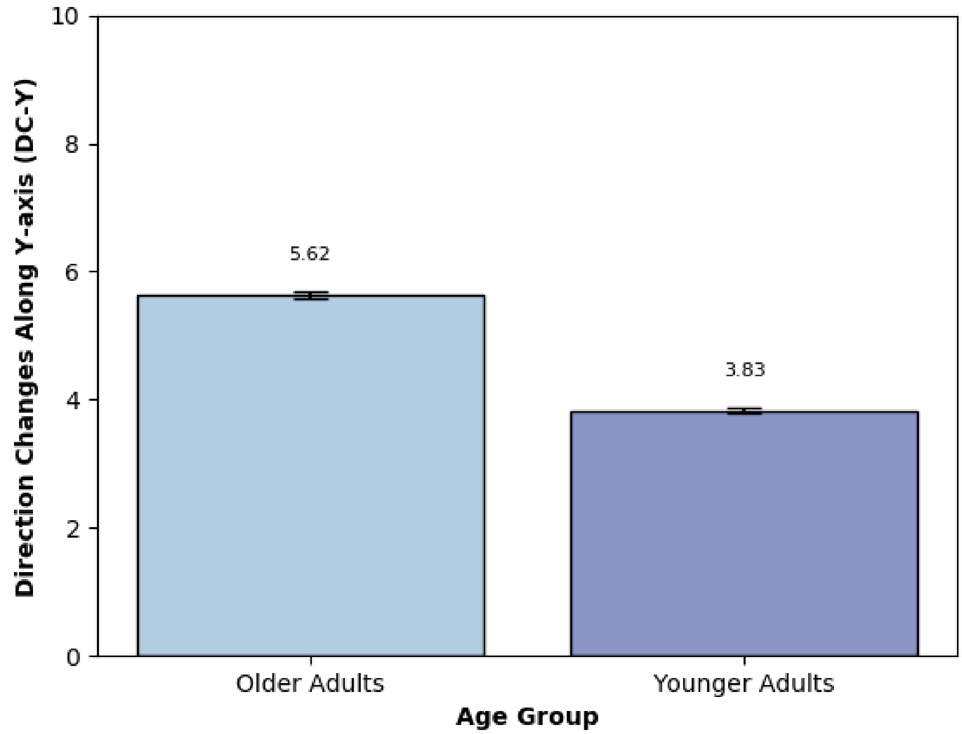


Figure 5.12 Mean direction change along y-axis (DC-Y) across age groups. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

and angles (see Table 5.5).

Main effect of target width was significant on DC-Z ($F_{2.43,67.93} = 3.70, p < .05, \eta_p^2 = .12$, see Figure 5.18). In individual age group the main effect of width was only observed for the older adults ($F_{3,26} = 4.17, p < .05, \eta_p^2 = .33$), but not for the younger adults (p = .864). The pairwise analysis reported significant differences in DC-Z between all pairs with the largest targets only in older adults (4.88 mm-12.22 mm: $p < .005$, 7.22 mm-12.22 mm: $p < .005$, 9.22 mm-12.22 mm: $p < .05$). We also observed an interaction effect of age × width ($F_{2.43,67.93} = 3.34, p < .05, \eta_p^2 = .11$, see Figure 5.19), highlighting that the disproportionate performance differences between age groups were reduced as the target widths increased.

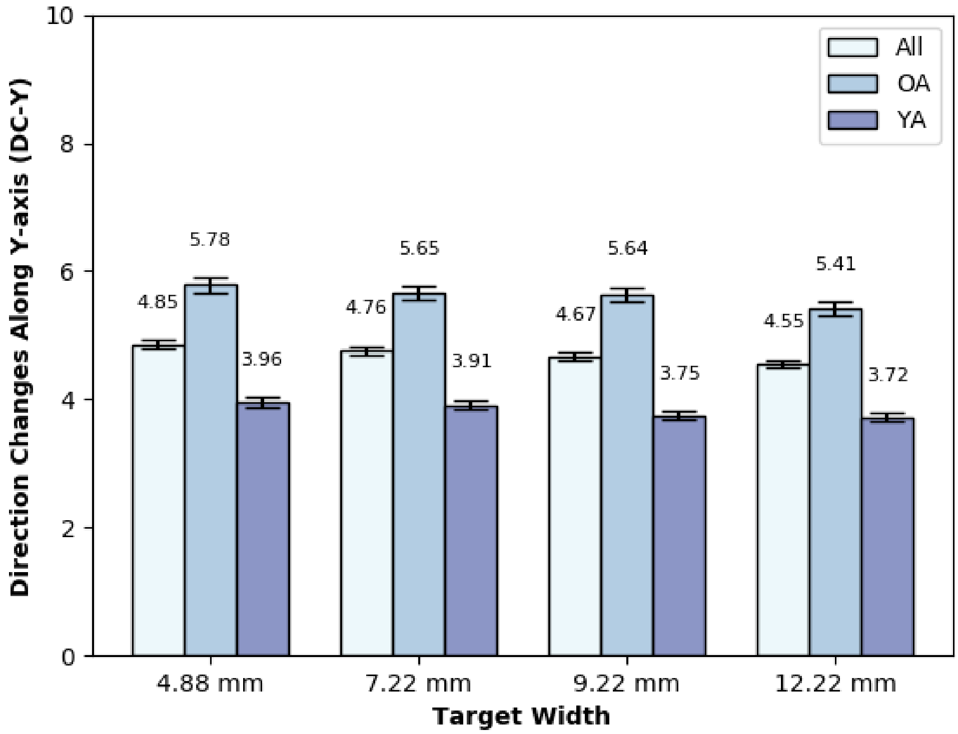


Figure 5.13 Mean direction change along y-axis (DC-Y) by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

We observed main effect of target amplitudes on DC-Z ($F_{2,56} = 20.47, p < .00001, \eta_p^2 = .42$, see Figure 5.20). Significant main effect of amplitudes was also reported in both older ($F_{2,27} = 9.91, p < .001, \eta_p^2 = .42$) and younger ($F_{2,27} = 7.10, p < .005, \eta_p^2 = .35$) adults. The pairwise differences were significant only for pairs with the 40 mm amplitudes in both older (20mm-40mm: $p < .001$, 30mm-40mm: $p < .0005$) and younger (20mm-40mm: $p < .005$, 30mm-40mm: $p < .05$) adults.

Main effect of target angle on DC-Z was also significant ($F_{4.82,134.82} = 24.66, p < .00001, \eta_p^2 = .47$, see Figure 5.21). Similar trend was observed in both individual age groups (older adults:

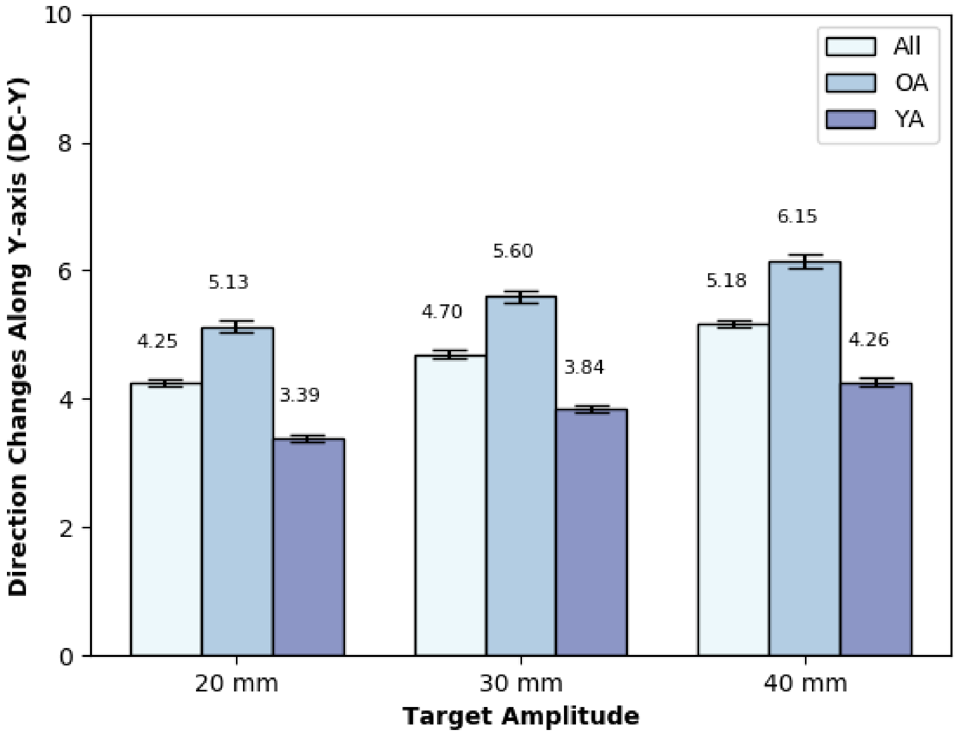


Figure 5.14 Mean direction changes along y-axis (DC-Y) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

$F_{7,22} = 13.22, p < .00001, \eta_p^2 = .81$; younger adults: $F_{7,22} = 12.09, p < .00001, \eta_p^2 = .79$). Moreover, there was an interaction effect of age × angle ($F_{4.82,134.82} = 5.90, p < .0001, \eta_p^2 = .17$, see Figure 5.22) that uncovered the disproportionate performance gaps between the older and younger adults for the targets located at the bottom-right quadrant (i.e., 270°, 315°, and 0° angles).

Movement Variability (MV)

Older adults had significantly higher movement variability (MV) than younger adults ($F_{1,28} = 6.57, p < .05, \eta_p^2 = .19$, see Figure 5.23). The age-related performance differences were signif-

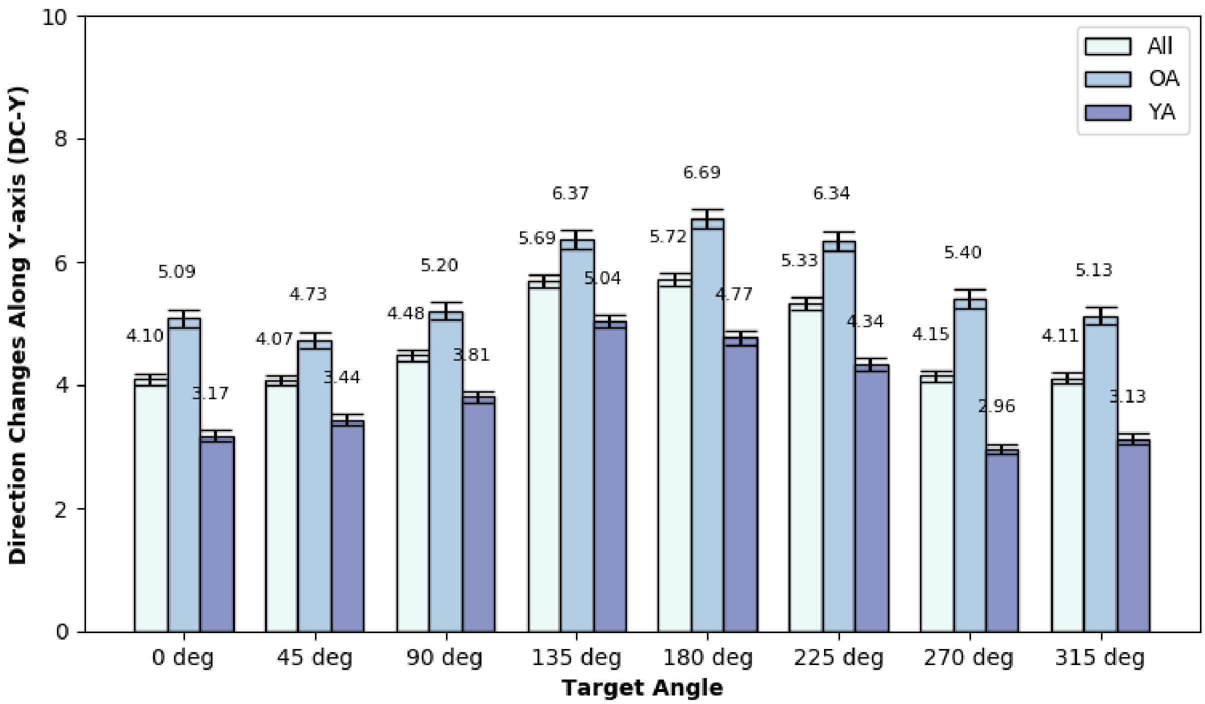


Figure 5.15 Mean direction changes along y-axis (DC-Y) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

icant across all target widths, and amplitudes (see Table 5.6). However, such performance differences were reported only for the targets located at the right side of the screen (90°, 45°, 0°, 315°, and 270°, see Table 5.6).

The main effect of target width was not significant on MV (all participants: $p = .779$; older adults: $p = .889$; younger adults: $p = .757$; see Figure 5.24). No pairwise performance difference between any width pairs was reported.

Target amplitude had main effect on MV (all participants: $F_{1.67,46.86} = 45.33, p < .00001, \eta_p^2 = .62$; older adults: $F_{2,27} = 10.89, p < .0005, \eta_p^2 = .45$; younger adults: $F_{2,27} = 21.50, p < .00001, \eta_p^2 = .61$, see Figure 5.25). Pairwise comparison showed significant differ-

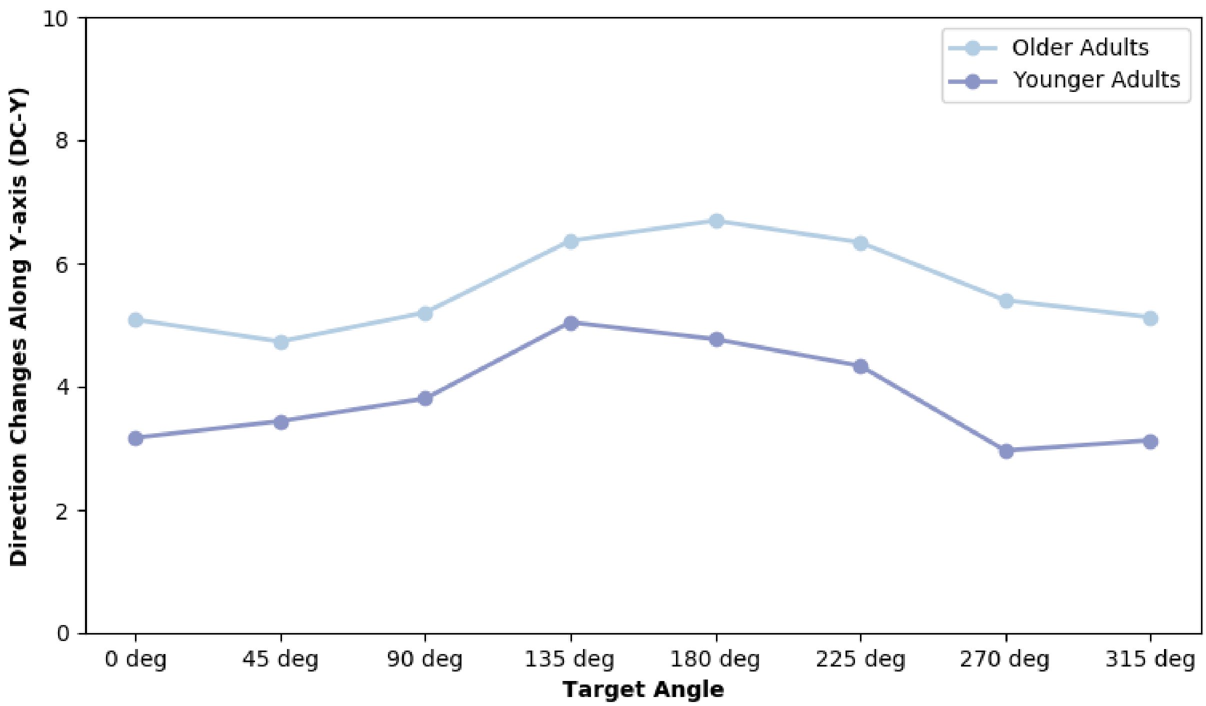


Figure 5.16 Interaction effect of age × angle on direction changes along y-axis (DC-Y). For both older and younger adults ($n = 16$).

Table 5.5 Age-related performance differences in movement direction changes along the z-axis (DC-Z) between older and younger adults.

Width (mm)	4.88	$F_{1,28} = 32.41$	$p < .00001$	$\eta_p^2 = .54$
	7.22	$F_{1,28} = 30.87$	$p < .00001$	$\eta_p^2 = .52$
	9.22	$F_{1,28} = 29.52$	$p < .00001$	$\eta_p^2 = .51$
	12.22	$F_{1,28} = 21.24$	$p < .0001$	$\eta_p^2 = .43$
Amplitude (mm)	20	$F_{1,28} = 30.74$	$p < .00005$	$\eta_p^2 = .52$
	30	$F_{1,28} = 27.49$	$p < .00001$	$\eta_p^2 = .50$
	40	$F_{1,28} = 28.71$	$p < .00001$	$\eta_p^2 = .51$
Angle (degree)	0	$F_{1,28} = 40.21$	$p < .00001$	$\eta_p^2 = .59$
	45	$F_{1,28} = 14.85$	$p < .001$	$\eta_p^2 = .35$
	90	$F_{1,28} = 15.60$	$p < .0005$	$\eta_p^2 = .36$
	135	$F_{1,28} = 11.61$	$p < .005$	$\eta_p^2 = .29$
	180	$F_{1,28} = 23.58$	$p < .00005$	$\eta_p^2 = .46$
	225	$F_{1,28} = 15.40$	$p < .001$	$\eta_p^2 = .36$
	270	$F_{1,28} = 40.94$	$p < .00001$	$\eta_p^2 = .59$
	315	$F_{1,28} = 39.18$	$p < .00001$	$\eta_p^2 = .58$

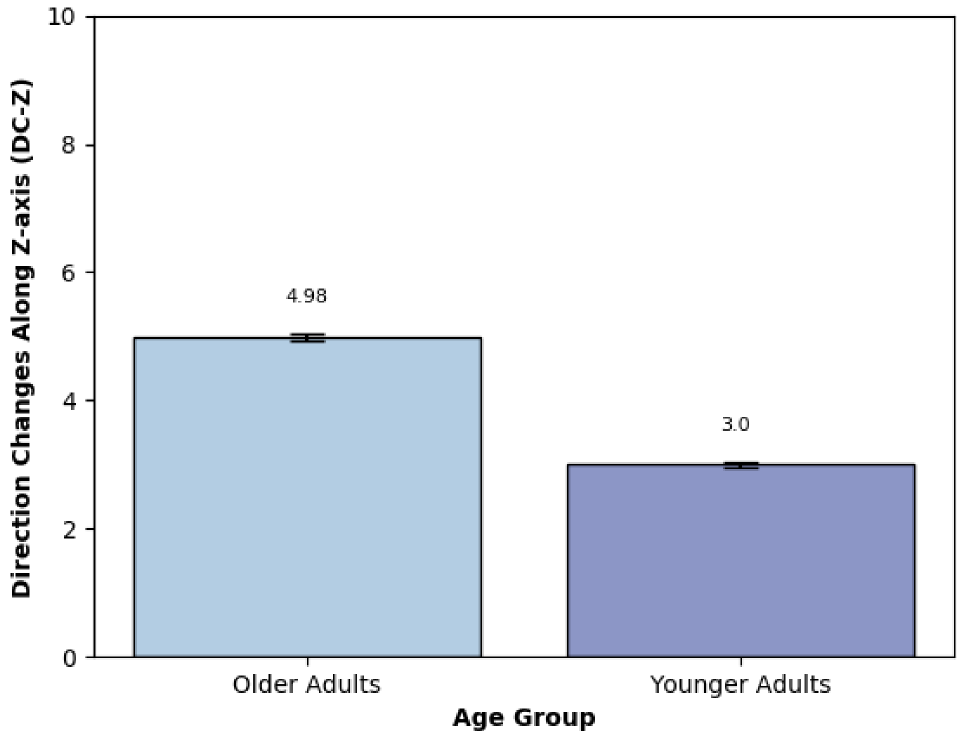


Figure 5.17 Mean direction changes along z-axis (DC-Z) by age group. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

ences between all amplitude pairs in both older ($p < .05$) and younger adults ($p < .005$).

We also observed significant main effect of target angles on MV (all participants: $F_{1.24,34.79} = 72.44, p < .00001, \eta_p^2 = .72$; older adults: $F_{7,22} = 6.07, p < .001, \eta_p^2 = .66$; younger adults: $F_{7,22} = 5.28, p < .001, \eta_p^2 = .63$; see Figure 5.26). Pairwise performance differences between the targets located at the right side and the left side of the screen were observed in both age groups ($p < .0005$), where targets at the left side (135°, 180° and 225°) had significantly higher MV.

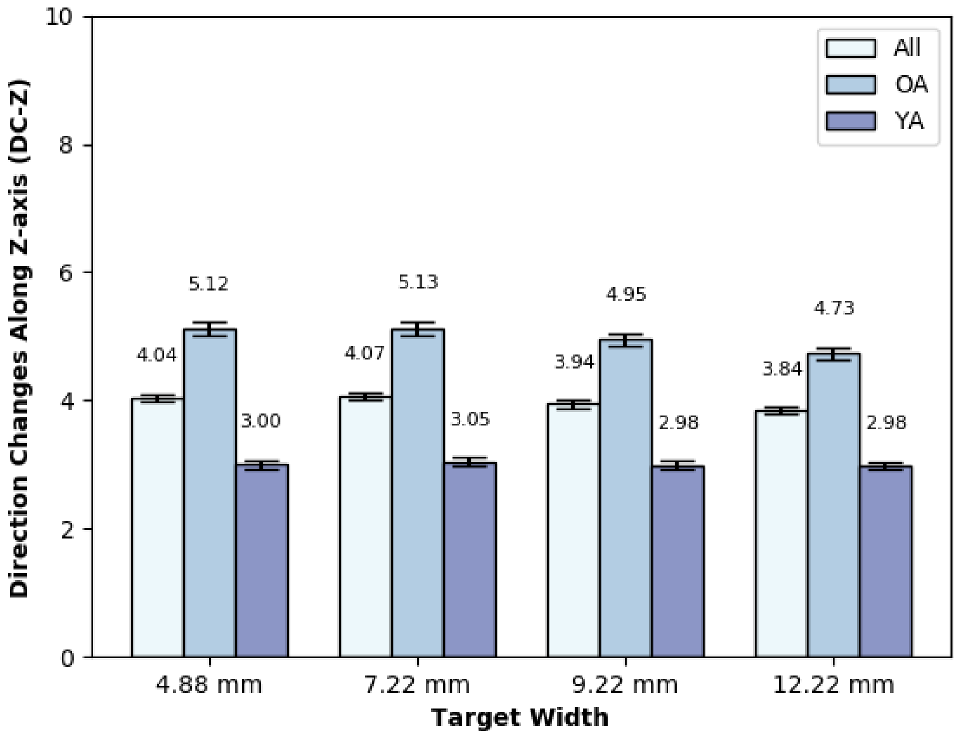


Figure 5.18 Mean direction change along z-axis (DC-Z) by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Path Axis Ratio (PAR)

Older adults had significantly higher path axis ratio (PAR) than younger adults ($F_{1,28} = 29.40, p < .00001, \eta_p^2 = .51$, see Figure 5.27). Age-related performance differences were also significant across all target widths, amplitudes, and angles (see Table 5.7).

No main effect of width on PAR was reported (all participants: $p = .309$, older adults: $p = .170$, younger adults: $p = .846$, see Figure 5.28). However, some pairwise differences between width pairs were evident in older adults (7.22 mm–9.22 mm: $p < .05$, 9.22 mm-12.22 mm: $p < .05$).

Table 5.6 Age-related performance differences in movement variability (MV) between older and younger adults.

Width (mm)	4.88	$F_{1,28} = 8.16$	$p < .01$	$\eta_p^2 = .23$
	7.22	$F_{1,28} = 5.03$	$p < .05$	$\eta_p^2 = .15$
	9.22	$F_{1,28} = 6.27$	$p < .05$	$\eta_p^2 = .18$
	12.22	$F_{1,28} = 6.37$	$p < .05$	$\eta_p^2 = .19$
Amplitude (mm)	20	$F_{1,28} = 8.14$	$p < .01$	$\eta_p^2 = .23$
	30	$F_{1,28} = 5.37$	$p < .05$	$\eta_p^2 = .16$
	40	$F_{1,28} = 5.85$	$p < .05$	$\eta_p^2 = .17$
Angle (degree)	0	$F_{1,28} = 15.61$	$p < .00001$	$\eta_p^2 = .36$
	45	$F_{1,28} = 8.42$	$p < .01$	$\eta_p^2 = .23$
	90	$F_{1,28} = 13.85$	$p < .001$	$\eta_p^2 = .33$
	135	not significant		
	180	not significant		
	225	not significant		
	270	$F_{1,28} = 14.35$	$p < .001$	$\eta_p^2 = .34$
	315	$F_{1,28} = 11.79$	$p < .005$	$\eta_p^2 = .30$

Table 5.7 Age-related performance differences in path axis ratio (PAR) between older and younger adults.

Width (mm)	4.88	$F_{1,28} = 33.56$	$p < .00001$	$\eta_p^2 = .55$
	7.22	$F_{1,28} = 27.50$	$p < .00005$	$\eta_p^2 = .50$
	9.22	$F_{1,28} = 27.00$	$p < .00005$	$\eta_p^2 = .49$
	12.22	$F_{1,28} = 26.54$	$p < .00005$	$\eta_p^2 = .49$
Amplitude (mm)	20	$F_{1,28} = 32.29$	$p < .00001$	$\eta_p^2 = .54$
	30	$F_{1,28} = 24.55$	$p < .00005$	$\eta_p^2 = .47$
	40	$F_{1,28} = 27.37$	$p < .00005$	$\eta_p^2 = .49$
Angle (degree)	0	$F_{1,28} = 30.19$	$p < .00001$	$\eta_p^2 = .52$
	45	$F_{1,28} = 19.51$	$p < .0005$	$\eta_p^2 = .41$
	90	$F_{1,28} = 29.55$	$p < .00001$	$\eta_p^2 = .51$
	135	$F_{1,28} = 19.81$	$p < .0005$	$\eta_p^2 = .41$
	180	$F_{1,28} = 16.72$	$p < .0005$	$\eta_p^2 = .37$
	225	$F_{1,28} = 21.47$	$p < .0001$	$\eta_p^2 = .43$
	270	$F_{1,28} = 33.73$	$p < .00001$	$\eta_p^2 = .55$
	315	$F_{1,28} = 37.89$	$p < .00001$	$\eta_p^2 = .58$

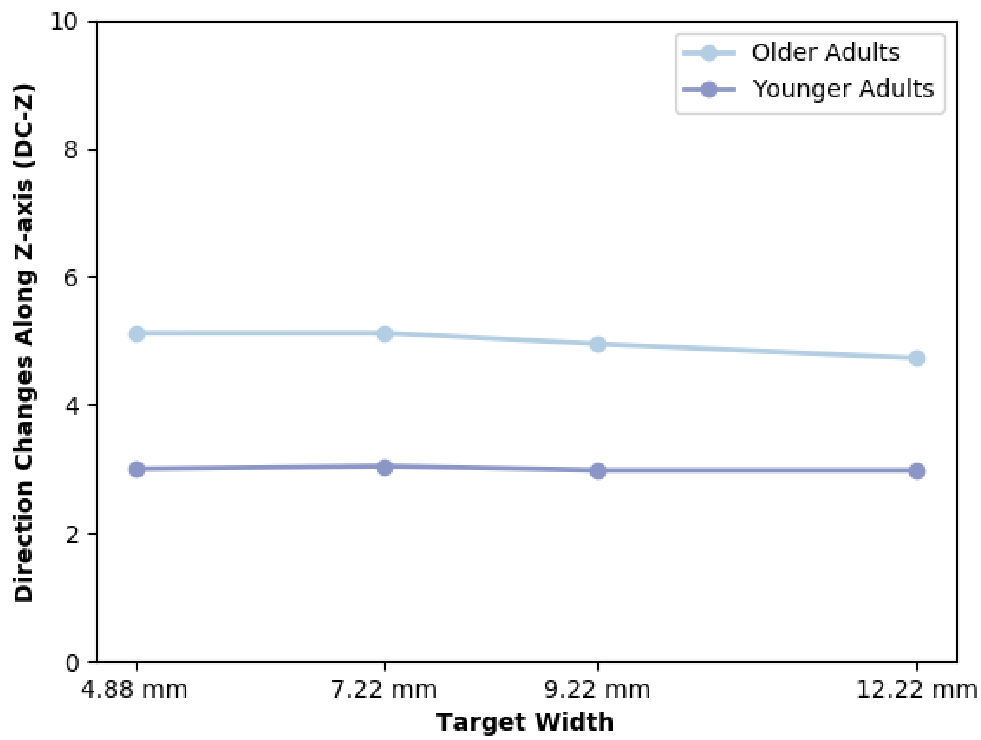


Figure 5.19 Interaction effect of age × width on direction change along z-axis (DC-Z). For both older and younger adults, $n = 16$.

We observed significant main effect of amplitude on PAR (all participants: $F_{1.44,40.20} = 149.24, p < .00001, \eta_p^2 = .84$; older adults: $F_{2,27} = 89.89, p < .00001, \eta_p^2 = .87$; younger adults: $F_{2,27} = 15.16, p < .00005, \eta_p^2 = .53$; see Figure 5.29). There were pairwise performance differences between all amplitude pairs in both age groups (older adults: $p < .00001$, younger adults: $p < .005$, for all pairs). We also observed an interaction effect of age × amplitude ($F_{1.44,40.20} = 26.47, p < .00001, \eta_p^2 = .49$, see Figure 5.30) on PAR that showed the performance gaps between two age groups reduced as amplitudes increases, unlike other measures – where longer amplitudes resulted in higher values in the measures.

Target angles also had main effect on PAR (all participants: $F_{4.09,114.60} = 43.70, p <$

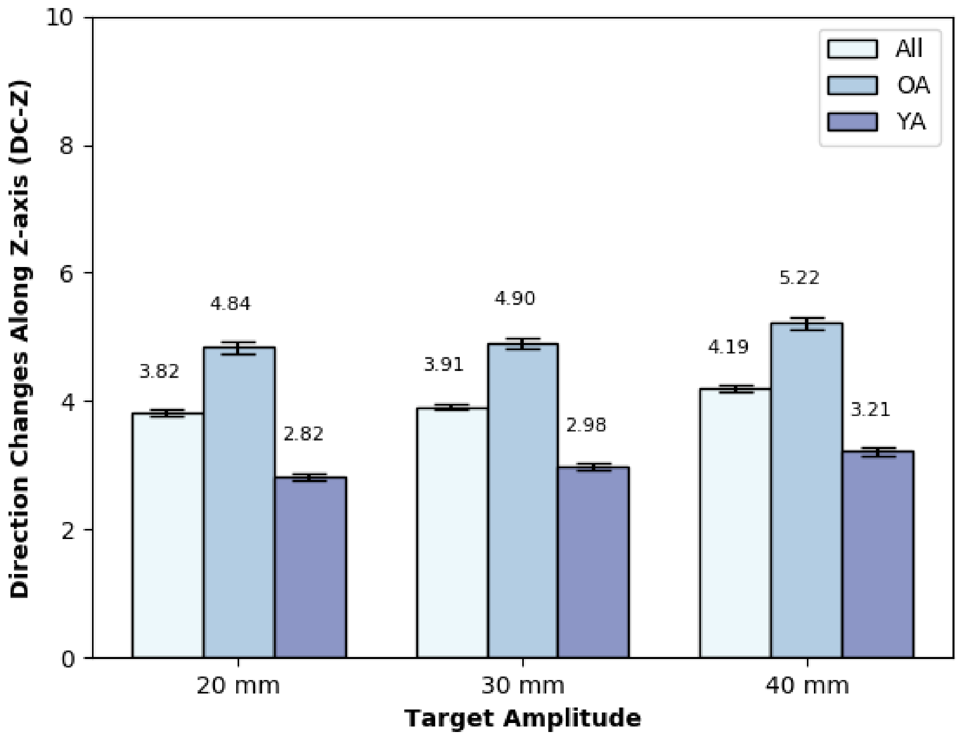


Figure 5.20 Mean direction changes along z-axis (DC-Z) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

$.00001, \eta_p^2 = .61$; older adults: $F_{7,22} = 20.81, p < .00001, \eta_p^2 = .87$; younger adults: $F_{7,22} = 9.42, p < .00005, \eta_p^2 = .75$; see Figure 5.31). Targets located at the bottom-half of the screen (180°, 225°, 227°, 315°, and 0°) had relatively higher PAR than targets located at the top-half of the screen. Significant pairwise performance differences were also observed across these locations in both older and younger adults ($p < .0005$ for all top-bottom pairs). We also observed an interaction effect of age × angle ($F_{4.09,114.60} = 3.67, p < .01, \eta_p^2 = .12$, see Figure 5.32) on PAR that demonstrated performance difference between age groups were disproportionately higher for the targets located at the bottom of the screen (225°, 270° and

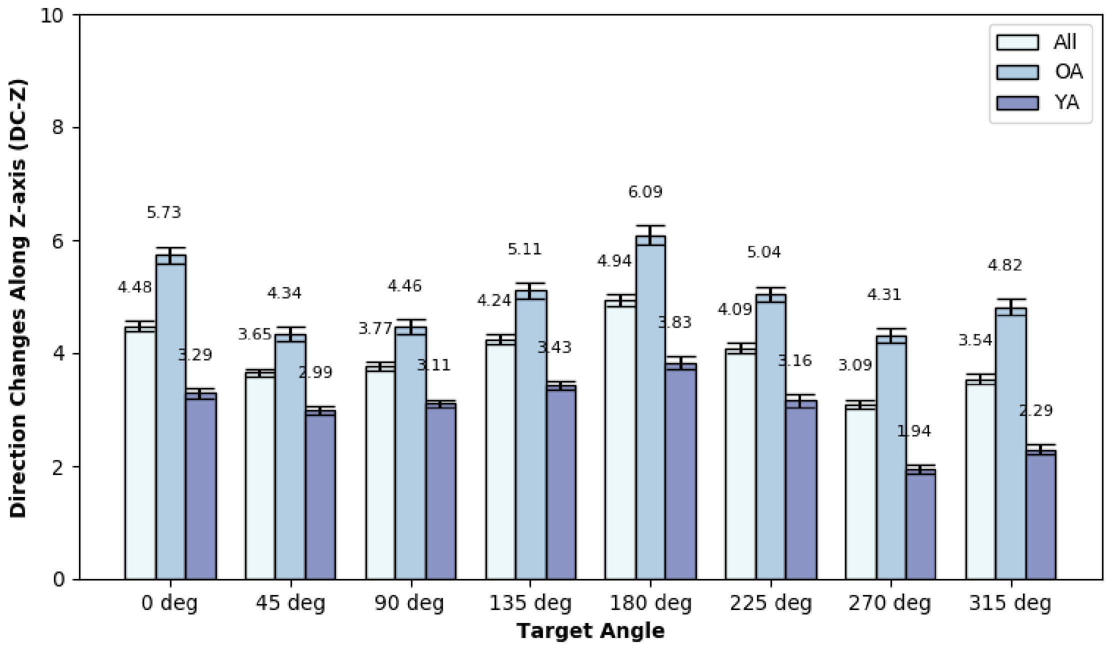


Figure 5.21 Mean direction changes along z-axis (DC-Z) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

315°) than the other target locations.

Pause Location Distance (PLD)

There was a significant main effect of age on pause location distance ($F_{1,28} = 4.26, p < .05, \eta_p^2 = .13$, see Figure 5.33). The age-related differences in PLD were significant only for the 12.22 mm width, 20 mm amplitude, and two horizontal locations: 0° and 180° angles (see Table 5.8).

Significant main effect of target width on PLD was observed for all participants ($F_{3,84} = 4.43, p < .01, \eta_p^2 = .14$, see Figure 5.34), and younger adults ($F_{3,26} = 4.42, p < .05, \eta_p^2 = .34$, but not for older adults ($p = .102$). However, the pairwise analysis across target widths

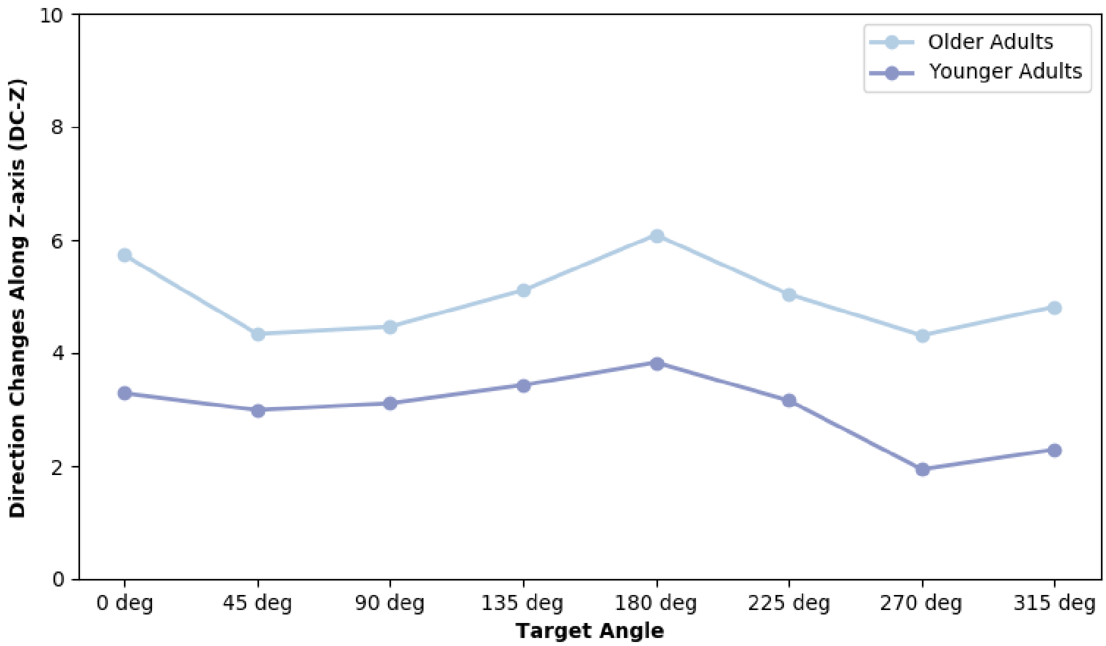


Figure 5.22 Interaction effect of age × angle on direction change along z-axis (DC-Z). For both older and younger adults, $n = 16$.

Table 5.8 Age-related performance differences in pause location distance (PLD) between older and younger adults.

Width (mm)	4.88	not significant		
	7.22	not significant		
	9.22	not significant		
	12.22	$F_{1,28} = 6.34$	$p < .05$	$\eta_p^2 = .19$
Amplitude (mm)	20	$F_{1,28} = 4.20$	$p < .05$	$\eta_p^2 = .52$
	30	not significant		
	40	not significant		
Angle (degree)	0	$F_{1,28} = 6.06$	$p < .05$	$\eta_p^2 = .18$
	45	not significant		
	90	not significant		
	135	not significant		
	180	$F_{1,28} = 10.01$	$p < .005$	$\eta_p^2 = .26$
	225	not significant		
	270	not significant		
	315	not significant		

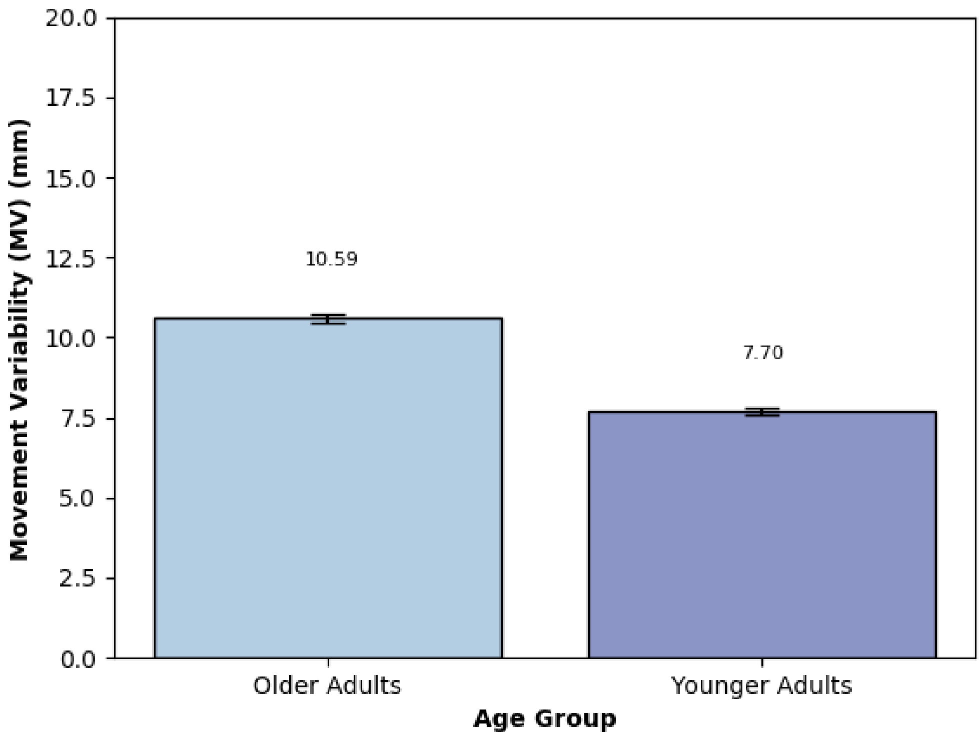


Figure 5.23 Mean movement variability (MV) by age group. For older adults, n = 16; for younger adults, n = 16. Error bars show the standard error.

reported significant differences between the 4.88mm-9.22mm ($p < .05$) width pairs for older adults. Although PLD decreased as target width increased, for older adults, PLD was higher in 12.22 mm targets than it was for the 9.22 mm targets. We calculated the PLD from the target centers (as it is defined in Hwang et al. (2005)), not from the target boundaries, which may not be ideal for targets as large as 9.22 mm and 12.22 mm. We recalculated PLD from the target boundaries and present in Table 5.9. After recalculating, PLD decreased in both age groups as target width increased. Moreover, for younger adults, pauses were taken very close to the target boundaries, plausibly for target verification before final selection, for targets with 7.22 mm width or larger. The negative PLD for 12.22 mm targets implies that

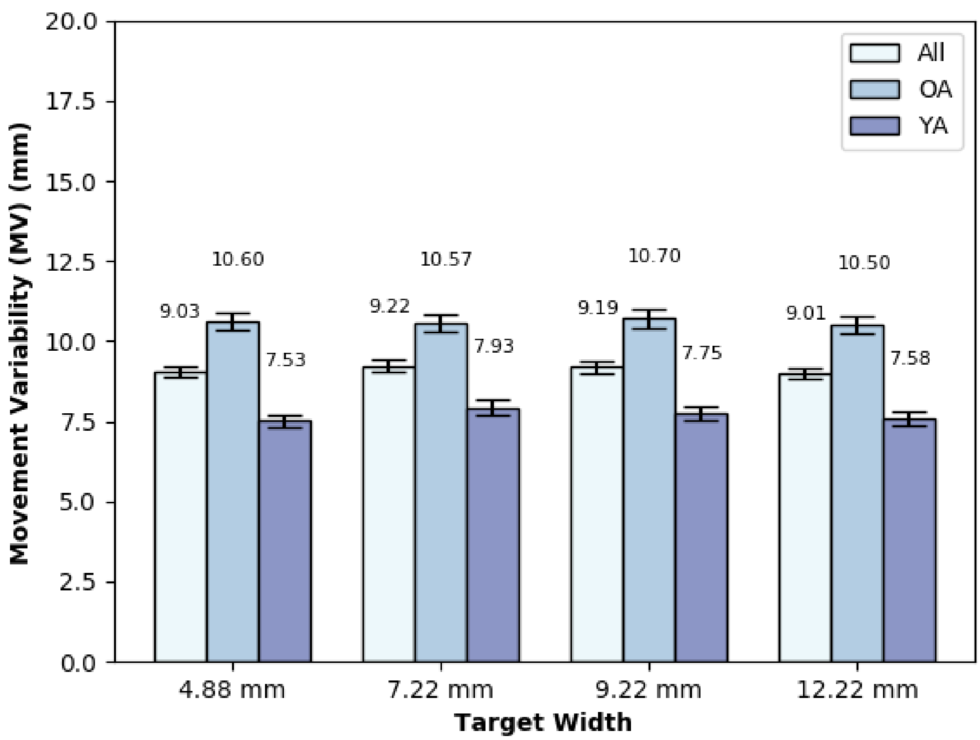


Figure 5.24 Mean movement variability (MV) by target width. For all participants, $N = 32$; for older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

younger adults more likely had a ballistic primary submovement. They paused and hovered only inside the target boundaries for target verification. However, older adults paused far from the target boundaries for all target widths. Such high PLD suggests that older adults had smaller submovements along the selection trajectories, unlike younger adults.

Table 5.9 Pause location distance (PLD) from Target boundaries across age groups.

Age Group	4.88 mm	7.22 mm	9.22 mm	12.22 mm
Older Adults	11.90	7.04	4.34	3.40
Younger Adults	8.12	2.83	0.23	-4.56

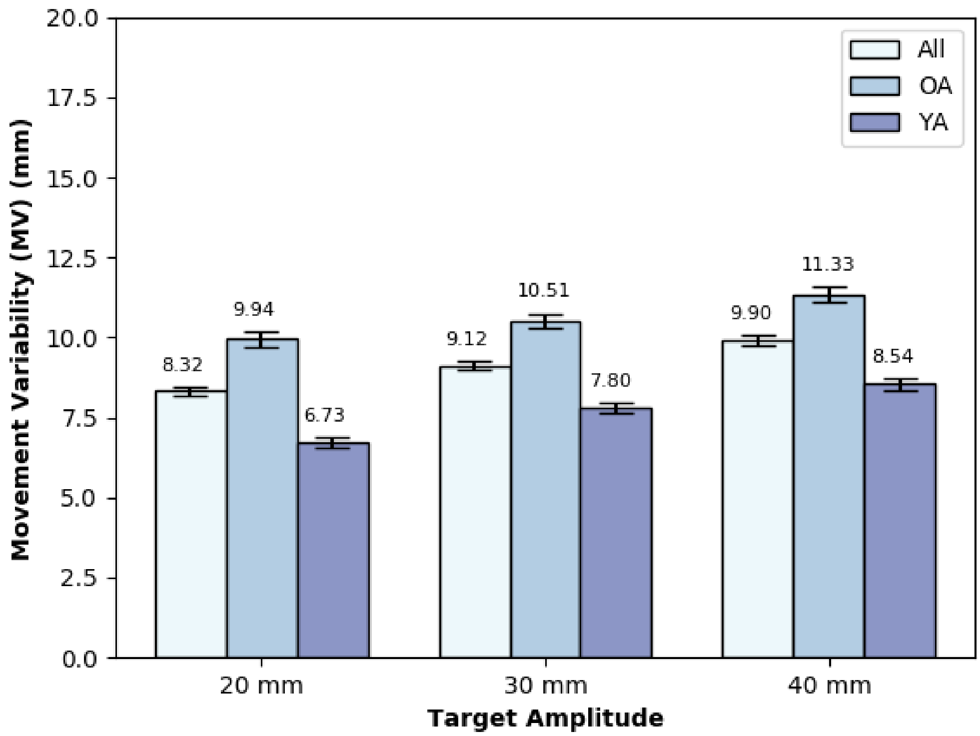


Figure 5.25 Mean movement variability (MV) by target amplitude. For all participants, $N = 32$; for older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

Main effect of target amplitudes was not significant on PLD (all participants: $F_{2,56} = 1.52, p = .228, \eta_p^2 = .05$; older adults: $F_{2,27} = 1.60, p = .220, \eta_p^2 = .11$; younger adults: $F_{2,27} = 0.31, p = .739, \eta_p^2 = .02$; see Figure 5.35). No pairwise performance difference was reported across target amplitudes in any age group.

Significant main effect of target angles was also observed on PLD ($F_{5.07,142.01} = 5.38, p < .0005, \eta_p^2 = .16$, see Figure 5.36). However, in individual age groups, no such significant main effect was observed (older adults: $p = .054$, younger adults: $p = .152$).

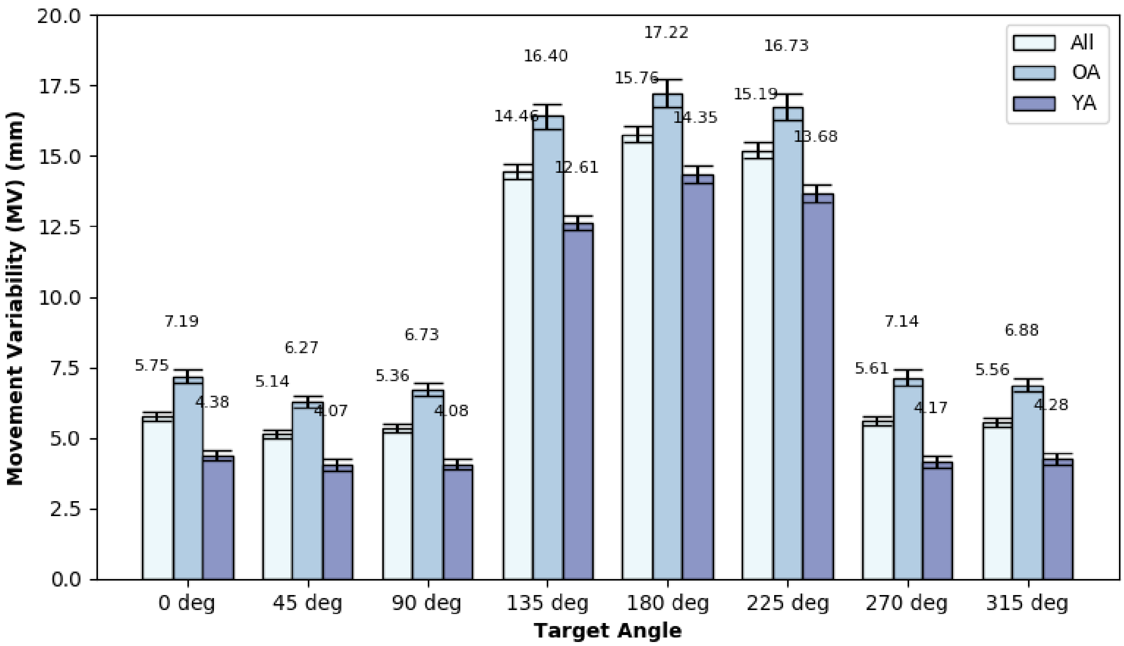


Figure 5.26 Mean movement variability (MV) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Peak Speed (SP)

Older adults had significantly higher peak speed (SP) than the younger adults ($F_{1,28} = 7.71, p < .01, \eta_p^2 = .22$, see Figure 5.37). The performance difference across age groups were significant for all target widths, all target amplitudes, and for the targets located at the bottom of the screen (0°, 225°, 270°, and 315°, see Table 5.10). These results do not align with prior works that reported lower peak speed in older adults with pen input (Ketcham et al., 2002), and individuals with motor impairments with mouse or trackball input (Wobbrock & Gajos, 2008), compared to younger adults with no motor impairments. While the reason for this difference is unclear, one possibility is that peak speed is influenced by a combination

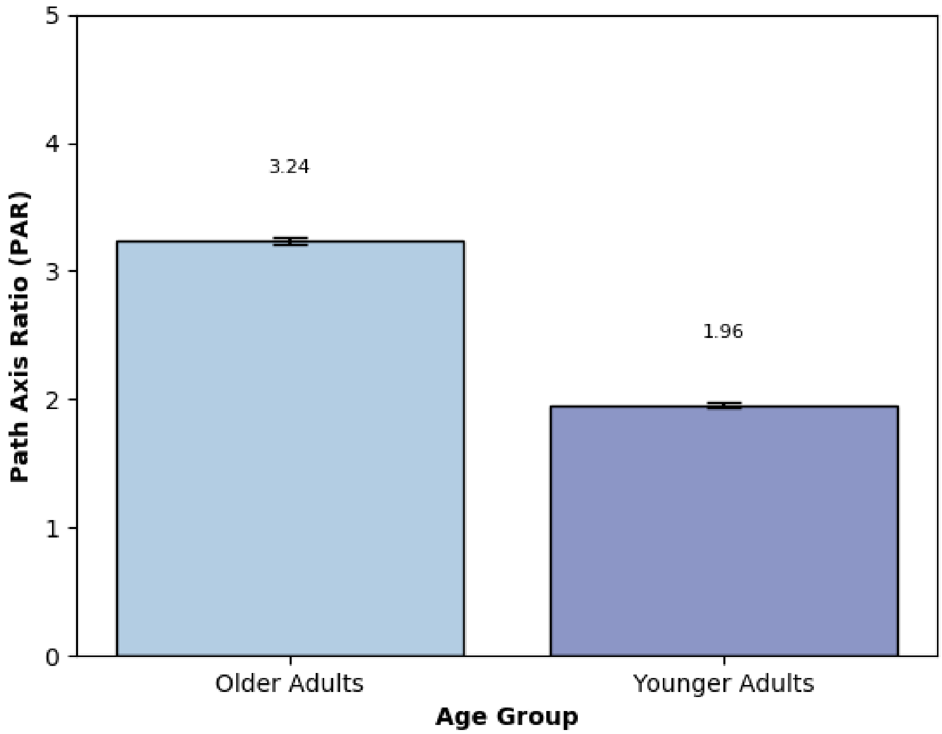


Figure 5.27 Mean path axis ratio (PAR) by age group. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

of factors including, the characteristics of the user population (e.g., severity and type of impairment), the device (e.g., size, weight, and form factor), and the physical movement of the hand (e.g., movement distance, and target size). We note that in Wobbrock and Gajos (2008) the participants had much more severe motor impairments than is typically associated with aging, and in Ketcham et al. (2002) participants were holding a light pen in midair which involves different muscle groups than touch interaction on a tablet.

We did not find any significant effect of width on SP (all participants: p = .672, older adults: p = .475, younger adults: p = .956, see Figure 5.38). No pairwise performance differences across widths were also observed.

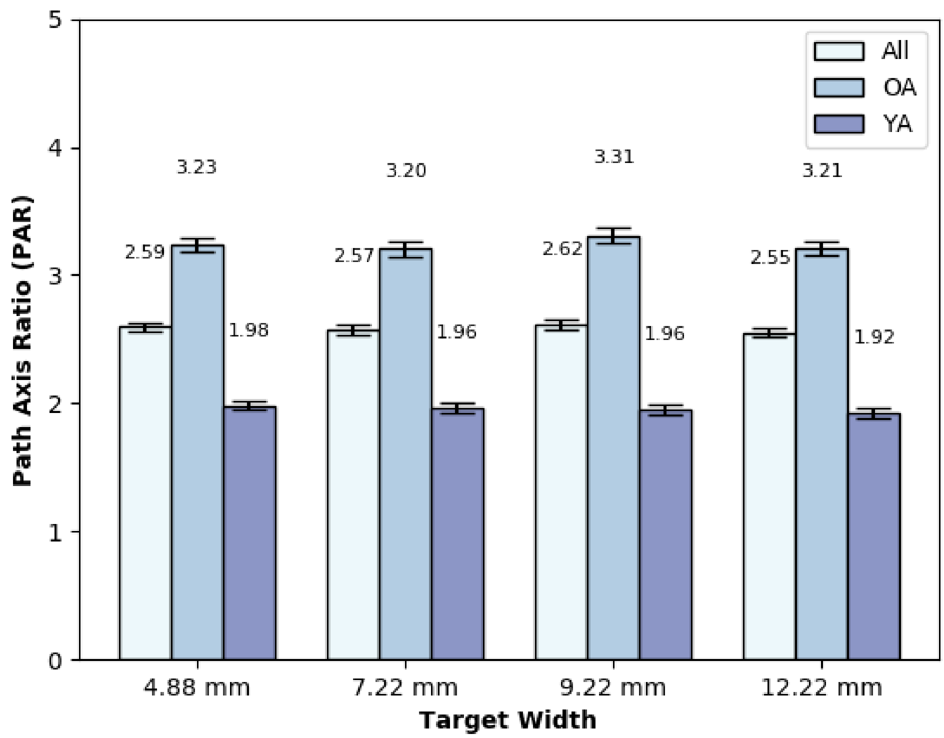


Figure 5.28 Mean path axis ratio (PAR) by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Target amplitudes had significant main effect on SP (all participants: $F_{1.60,44.81} = 36.77, p < .00001, \eta_p^2 = .57$; older adults: $F_{2,27} = 20.09, p < .00001, \eta_p^2 = .60$; younger adults: $F_{2,27} = 42.21, p < .00001, \eta_p^2 = .76$). Pairwise differences across all amplitudes were also evident in both individual age groups ($p < .05$ in both age groups for all amplitude pairs, see Figure 5.39).

Significant main effect of target angles on SP was also observed for all participants ($F_{7,196} = 7.20, p < .00001, \eta_p^2 = .21$) and older adults ($F_{7,22} = 6.90, p < .0005, \eta_p^2 = .69$), but not for younger adults ($F_{7,196} = 1.72, p = .156, \eta_p^2 = .35$, see Figure 5.40). The pairwise analysis found significant differences ($p < .05$) in SP between the targets located at the top

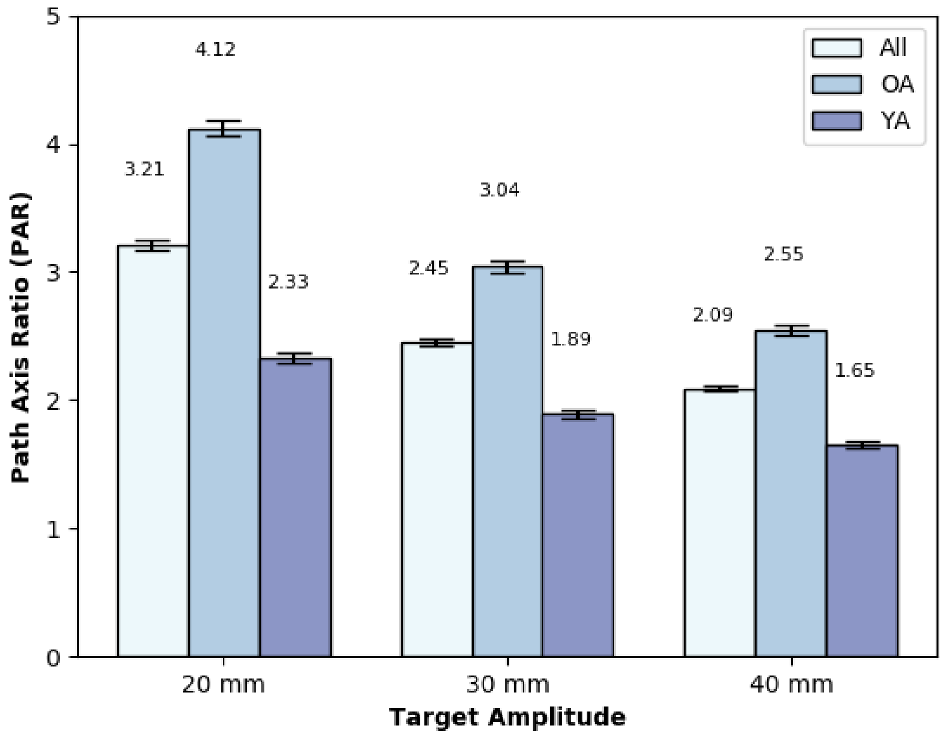


Figure 5.29 Mean path axis ratio (PAR) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

half of the screen (45°, 90°, 135°) and the targets located at the bottom half of the screen (225°, 270°, 315°) only in older adults, where SP was higher at the targets at the bottom half of the screen. No such pairwise differences were observed in younger adults. The interaction effect of age × angle ($F_{7,196} = 4.13, p < .0005, \eta_p^2 = .13$, see Figure 5.41) confirmed that older adults had disproportionately higher SP for selecting targets located at the bottom-right quadrant (270° and 315°), compared to the younger adults.

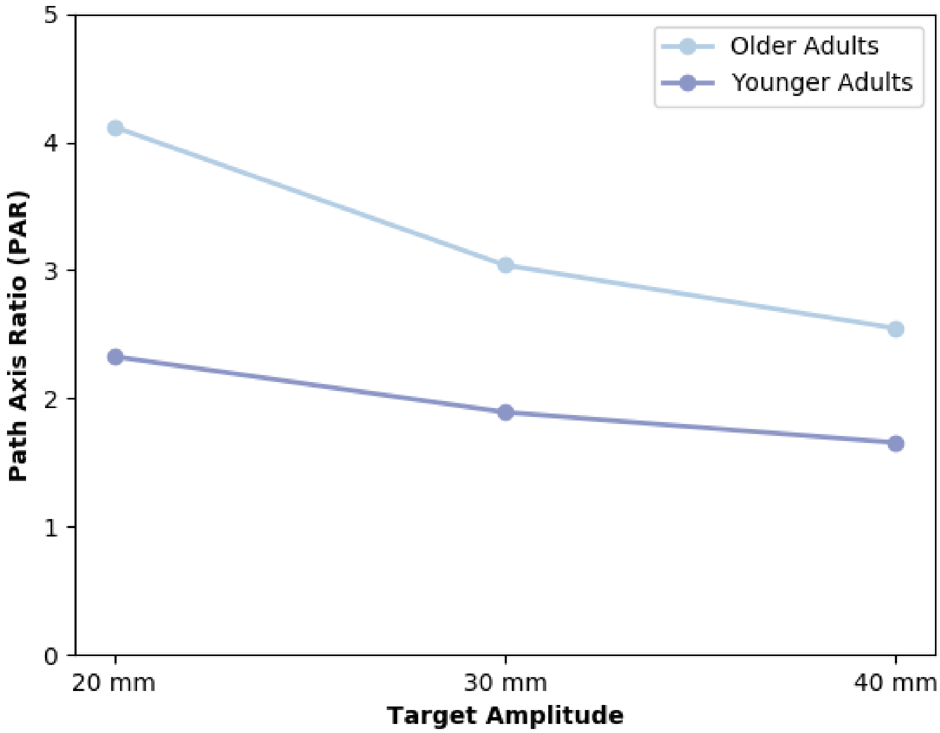


Figure 5.30 Interaction effect of age × amplitude on path axis ratio (PAR). For both older and younger adults, $n = 16$.

Mean Roll (RR)

Older adults had significantly higher mean roll (RR) per trial than younger adults ($F_{1,28} = 6.00, p < .05, \eta_p^2 = .18$, see Figure 5.42). Pairwise differences between age groups were also significant across all target widths, amplitudes, and all angles, except for the 0° angle (see Table 5.11).

We did not find any main effect of target widths on RR (all participants: $p = .832$, older adults: $p = .930$, younger adults: $p = .812$, see Figure 5.43). No pairwise difference was also observed across target widths in any individual age group.

No main effect of target amplitudes was observed on RR (all participants: $p = .709$,

Table 5.10 Age-related performance differences in peak speed (SP) between older and younger adults.

Width (mm)	4.88	$F_{1,28} = 7.10$	$p < .05$	$\eta_p^2 = .20$
	7.22	$F_{1,28} = 6.31$	$p < .05$	$\eta_p^2 = .18$
	9.22	$F_{1,28} = 7.68$	$p < .05$	$\eta_p^2 = .22$
	12.22	$F_{1,28} = 7.51$	$p < .05$	$\eta_p^2 = .21$
Amplitude (mm)	20	$F_{1,28} = 11.59$	$p < .005$	$\eta_p^2 = .29$
	30	$F_{1,28} = 6.92$	$p < .05$	$\eta_p^2 = .20$
	40	$F_{1,28} = 5.01$	$p < .05$	$\eta_p^2 = .15$
Angle (degree)	0	$F_{1,28} = 6.86$	$p < .05$	$\eta_p^2 = .20$
	45	not significant		
	90	not significant		
	135	not significant		
	180	not significant		
	225	$F_{1,28} = 4.98$	$p < .05$	$\eta_p^2 = .15$
	270	$F_{1,28} = 20.94$	$p < .0005$	$\eta_p^2 = .43$
	315	$F_{1,28} = 15.59$	$p < .0005$	$\eta_p^2 = .36$

Table 5.11 Age-related performance differences in mean roll (RR) between older and younger adults.

Width (mm)	4.88	$F_{1,28} = 5.35$	$p < .05$	$\eta_p^2 = .16$
	7.22	$F_{1,28} = 5.91$	$p < .05$	$\eta_p^2 = .17$
	9.22	$F_{1,28} = 5.89$	$p < .05$	$\eta_p^2 = .17$
	12.22	$F_{1,28} = 6.33$	$p < .05$	$\eta_p^2 = .18$
Amplitude (mm)	20	$F_{1,28} = 5.53$	$p < .05$	$\eta_p^2 = .17$
	30	$F_{1,28} = 5.64$	$p < .05$	$\eta_p^2 = .17$
	40	$F_{1,28} = 6.52$	$p < .05$	$\eta_p^2 = .19$
Angle (degree)	0	not significant		
	45	$F_{1,28} = 5.33$	$p < .05$	$\eta_p^2 = .16$
	90	$F_{1,28} = 6.47$	$p < .05$	$\eta_p^2 = .51$
	135	$F_{1,28} = 7.13$	$p < .05$	$\eta_p^2 = .20$
	180	$F_{1,28} = 8.02$	$p < .01$	$\eta_p^2 = .22$
	225	$F_{1,28} = 4.96$	$p < .05$	$\eta_p^2 = .15$
	270	$F_{1,28} = 4.78$	$p < .05$	$\eta_p^2 = .15$
	315	$F_{1,28} = 4.63$	$p < .05$	$\eta_p^2 = .14$

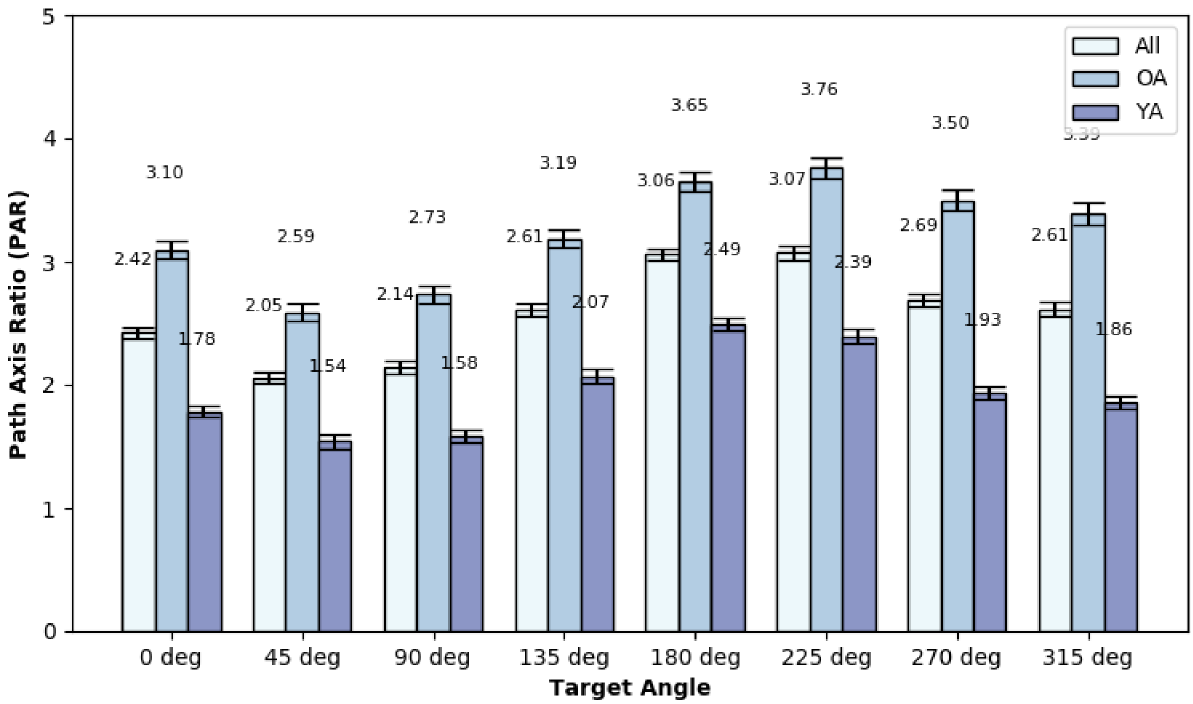


Figure 5.31 Mean path axis ratio (PAR) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

older adults: $p = .813$, younger adults: $p = .912$, see Figure 5.44). We also did not find any pairwise differences across target width in both older and younger adults.

We observed main effect of target angle on RR (all participants: $F_{7,196} = 18.32, p < .00001, \eta_p^2 = .40$; older adults: $F_{7,22} = 14.61, p < .00001, \eta_p^2 = .82$; younger adults: $F_{7,22} = 6.66, p < .0005, \eta_p^2 = .68$). Some pairwise performance differences were observed between targets located at the left side and the right side of the screen in both older and younger adults (see Figure 5.45).

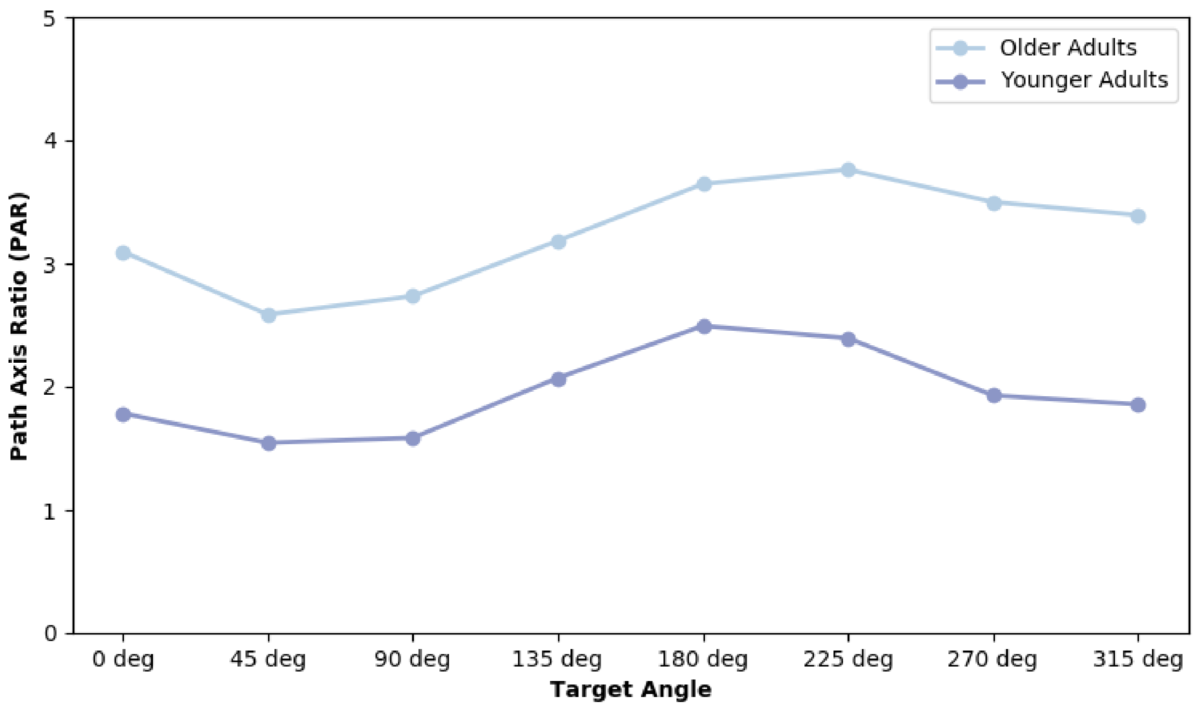


Figure 5.32 Interaction effect of age × angle on path axis ratio (PAR). For both older and younger adults, $n = 16$.

Summary

We summarized the complete ANOVA analysis of the finger trajectory measures in Table 5.12. A Y in that table represents that a significant main or interaction effect of the corresponding factor (e.g., age, width, etc., listed in the columns) was observed on the corresponding measure (listed in the rows). Among the sixteen finger trajectory measures, eight of them demonstrated significant performance differences across age groups. These measures are: direction changes along all axes (DC-X, DC-Y, and DC-Z), movement variability (MV), path axis ratio (PAR), pause location distance (PLD), peak speed (SP), and finger roll (RR). Our analysis further revealed that older and younger adults had significant

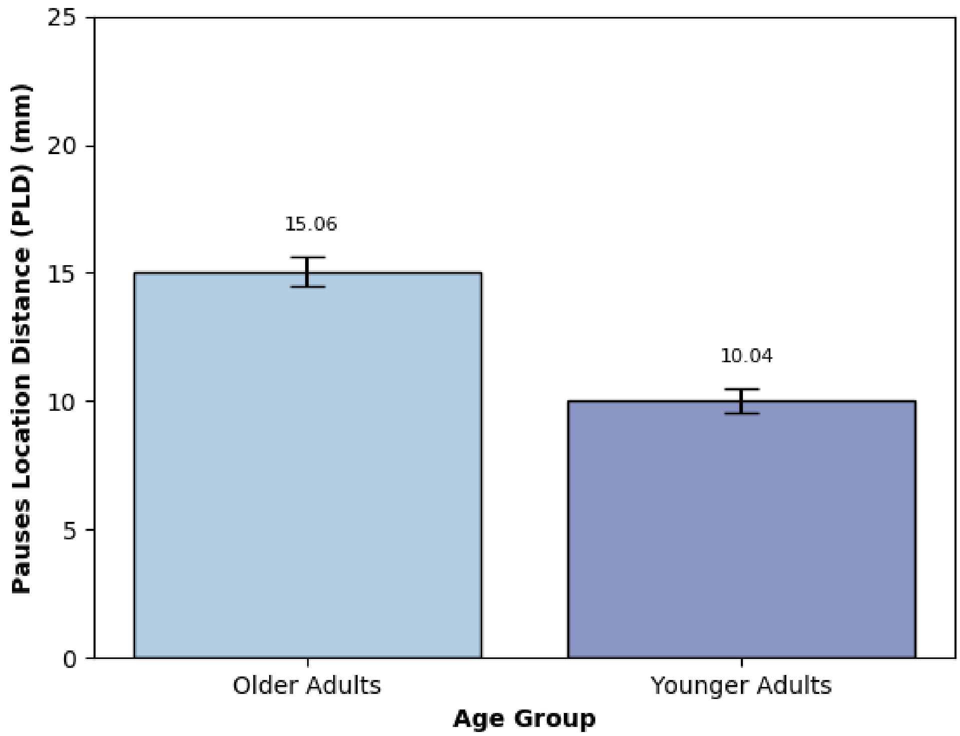


Figure 5.33 Mean pause location distance (PLD) per trial from the center of the target by age group. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

pairwise performance differences in these measures, across most of the target widths (Table 5.13), amplitudes (Table 5.14), and angles (Table 5.15). The following paragraphs provide the summary of the performance difference between older and younger adults, across widths, amplitudes, and angles for these eight measures.

Target Width. Significant pairwise performance differences were observed between older and younger adults, across all target widths, in seven out of these eight trajectory measures (see Table 5.13). The only exception was pause location distance (PLD) having age-related performance differences only for the 12.22 mm targets. We observed significant

Table 5.12 Summary of the inferential statistics for the finger trajectory measures. A "Y" in the cell represents presence of significant performance difference for the corresponding factor and measure.

Trajectory Measures	**Age**	**Width**	**Amplitude**	**Angle**	**Age × Width**	**Age × Amplitude**	**Age × Angle**
DC-X	Y	Y	Y	Y			Y
DC-Y	Y	Y	Y	Y			Y
DC-Z	Y	Y	Y	Y	Y		Y
TPC			Y	Y			
MV	Y		Y	Y			
MO			Y	Y			
ME							
PAR	Y		Y	Y		Y	Y
PF		Y					
PD		Y	Y				
PLD	Y	Y		Y			
SP	Y		Y	Y			
SM		Y	Y	Y		Y	Y
RP				Y			
RY				Y			
RR	Y			Y			

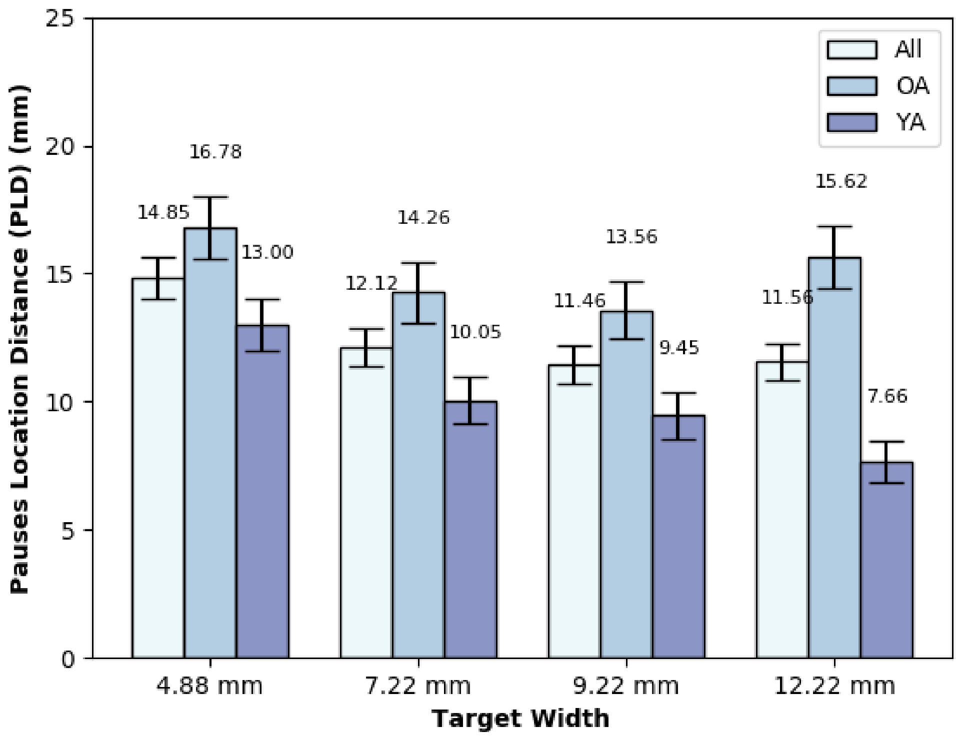


Figure 5.34 Mean pause location distance (PLD) per trial from the center of the target, by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

interaction effect of age × width only on direction changes along the z-axis (DC-Z), where older adults disproportionately had higher counts in DC-Z with the smaller targets. In general, values of the trajectory measures increased as target width decreased for both older and younger adults. However, pairwise performance differences across width pairs were not significant in younger adults, demonstrating that target size did not pose any barrier towards their selection performance. On the contrary, in older adults, significant pairwise performance differences were observed across many width pairs, especially pairs involving the largest targets (12.22 mm). In particular, we observed performance differences in older adults

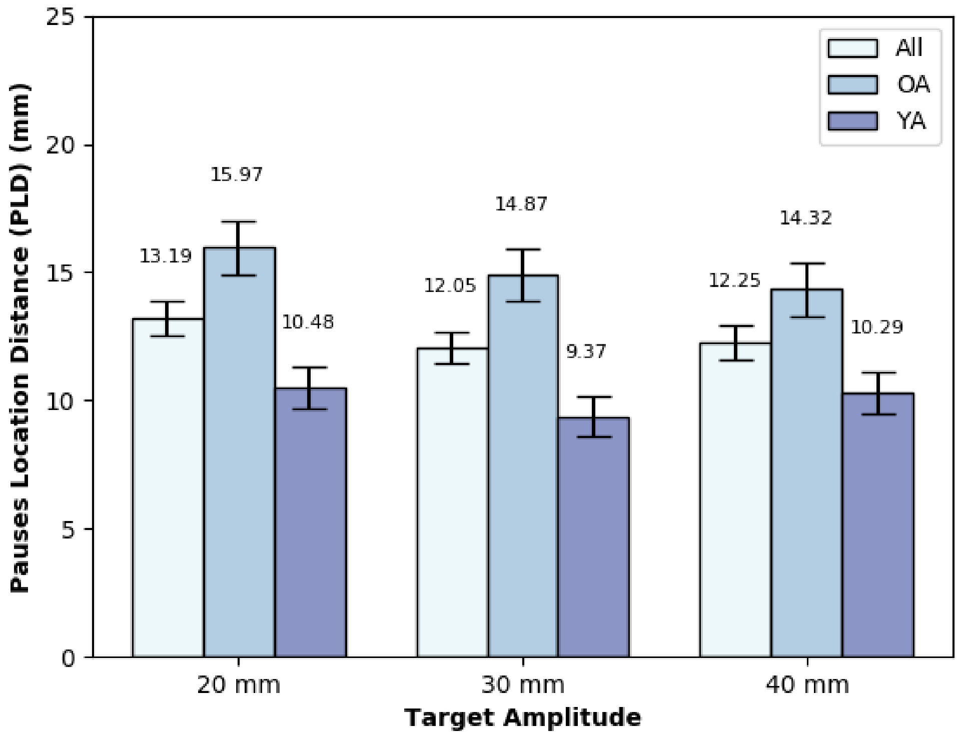


Figure 5.35 Mean pause location distance (PLD) per trial from the center of the target, by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

for the following width pairs: 4.88mm-9.22mm (pause location distance (PLD)), 4.88mm-12.22mm (direction changes along all axes (DC-X, DC-Y, DC-Z)), 7.22mm-9.22mm (path axis ratio (PAR)), 7.22mm-12.22mm (direction changes along all axes (DC-X, DC-Y, DC-Z)), and 9.22mm-12.22mm (direction changes along z-axis (DC-Z), path axis ratio (PAR)). No pairwise performance differences were observed between the 4.88 mm and 7.22 mm targets in that age group, showing that increasing the target size from 4.88 mm to 7.22 mm did not significantly improve the performance of older adults. To improve selection performance, targets needed to be at least as large as 9.22 mm.

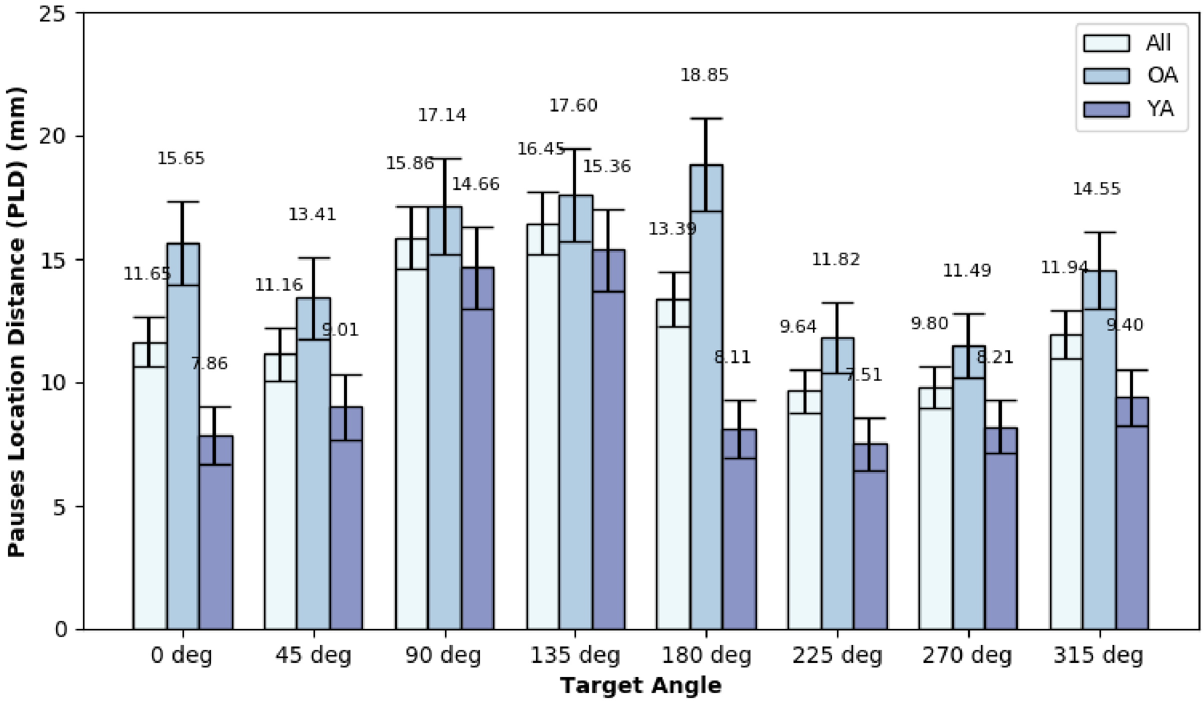


Figure 5.36 Mean pause location distance (PLD) per trial from the center of the target, by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Table 5.13 Pairwise performance differences across age groups by target widths. A "Y" in the cell represents presence of significant performance difference between older and younger adults, for the corresponding width and measure.

	Target Width (mm)			
Trajectory Measures	**4.88**	**7.22**	**9.22**	**12.22**
DC-X	Y	Y	Y	Y
DC-Y	Y	Y	Y	Y
DC-Z	Y	Y	Y	Y
MV	Y	Y	Y	Y
PAR	Y	Y	Y	Y
PLD				Y
SP	Y	Y	Y	Y
RR	Y	Y	Y	Y

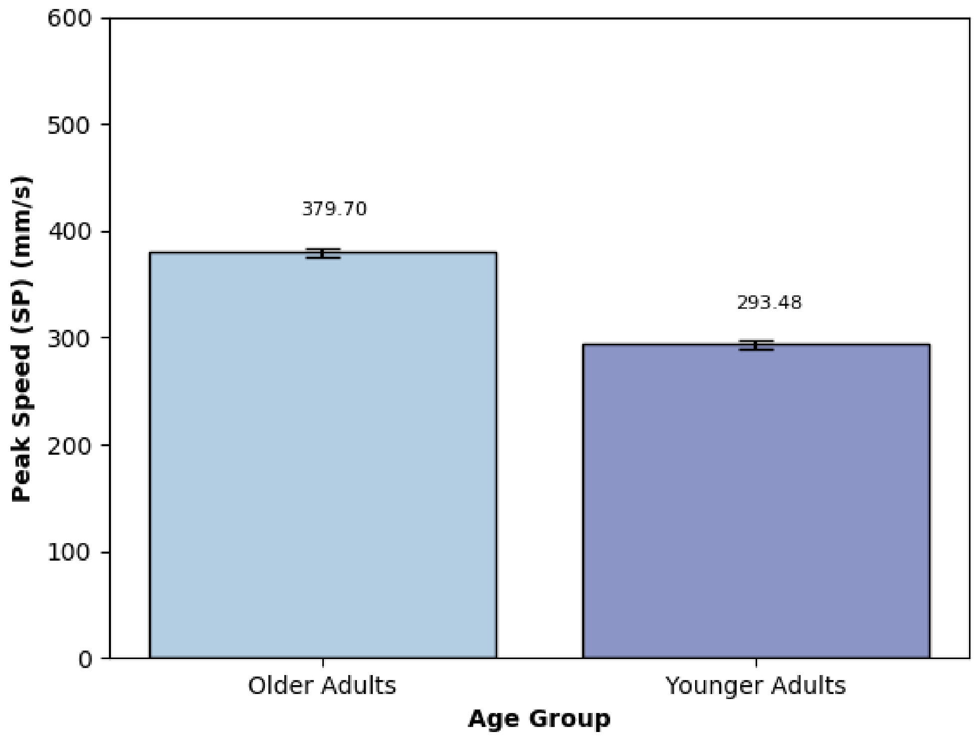


Figure 5.37 Mean peak speed (SP) by age group. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

Target Amplitude. We observed significant performance differences between age groups in seven out of these eight finger trajectory measures, across all target amplitudes (Table 5.14). The only exception was pause location distance (PLD), where such performance difference was observed only for the 20 mm amplitudes. The interaction effect of age $\times$ amplitude was observed for path axis ratio (PAR), were unlike other measures, older adults disproportionately had higher PAR in the smaller amplitudes. Values in the finger trajectory measures generally increased as the amplitude increased in both age groups. Significant pairwise performance differences across amplitudes were observed in both older and younger adults. We observed significant pairwise performance differences for the following ampli-

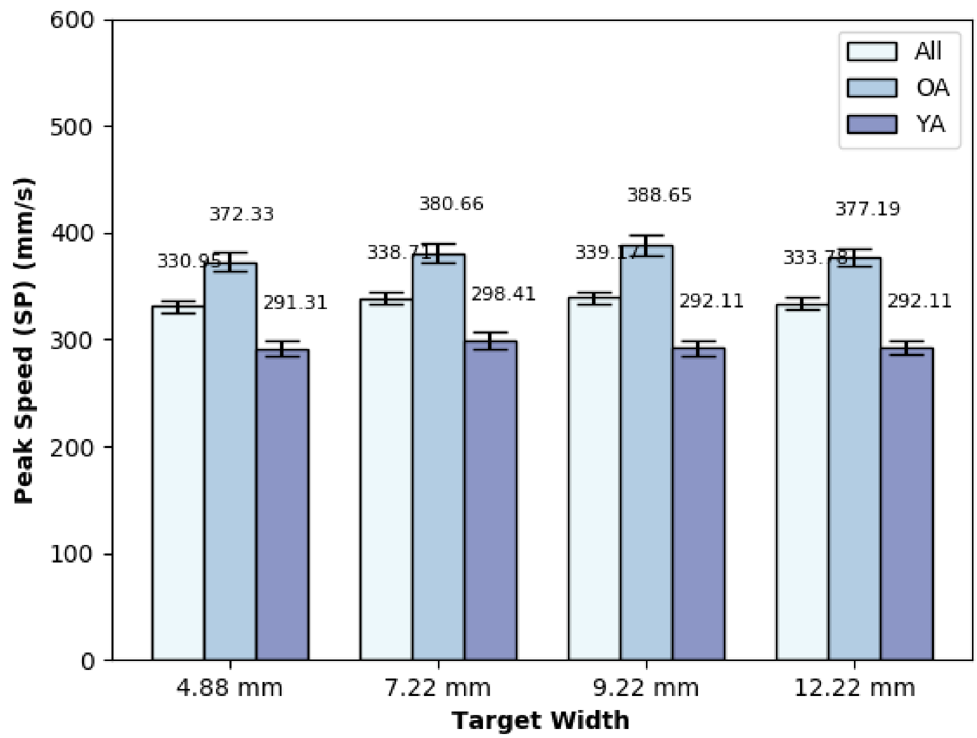


Figure 5.38 Mean peak speed (SP) by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

tude pairs for both older and younger adults: 20mm-30mm (direction changes along y-axis (DC-Y), movement variability (MV), path axis ratio (PAR), peak speed (SP)), 20mm-40mm (direction changes along all axes (DC-X, DC-Y, DC-Z), movement variability (MV), path axis ratio (PAR), peak speed (SP)), 30mm-40mm (direction changes along y- and z-axis (DC-Y, DC-Z), movement variability (MV), path axis ratio (PAR), peak speed (SP)). These results demonstrate that unlike target widths, both older and younger adults encountered selection difficulties as target amplitude increased.

Target Angle. Significant pairwise performance differences between older and younger adults were observed across all target angles only for direction changes along all axes (DC-X,

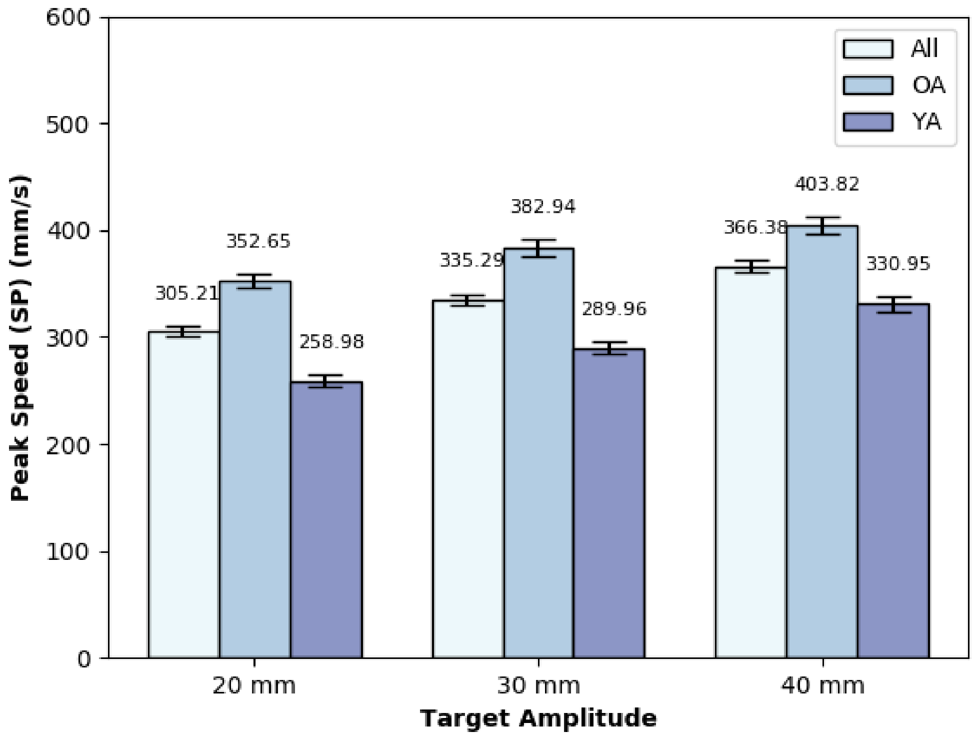


Figure 5.39 Mean peak speed (SP) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Table 5.14 Pairwise performance differences across age groups by target amplitudes. A "Y" in the cell represents presence of significant performance difference between older and younger adults, for the corresponding amplitude and measure.

	Target Amplitude (mm)		
Trajectory Measures	**20**	**30**	**40**
DC-X	Y	Y	Y
DC-Y	Y	Y	Y
DC-Z	Y	Y	Y
MV	Y	Y	Y
PAR	Y	Y	Y
PLD	Y		
SP	Y	Y	Y
RR	Y	Y	Y

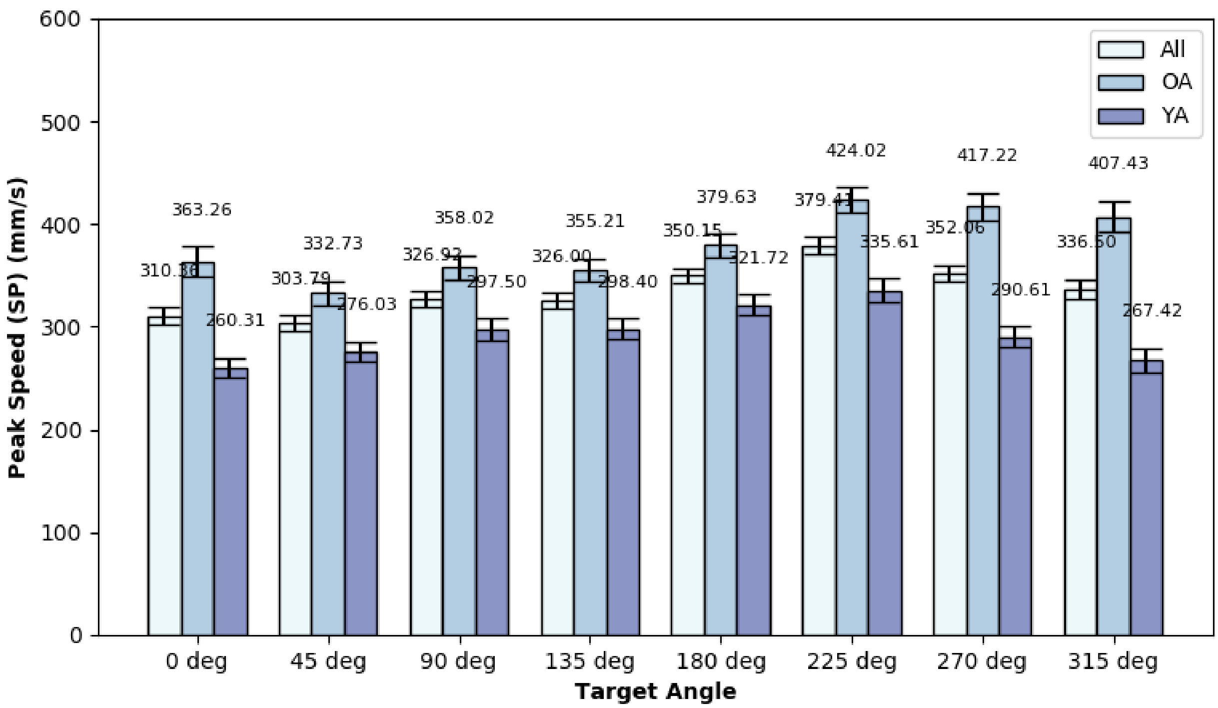


Figure 5.40 Mean peak speed (SP) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

DC-Y, DC-Z), and path axis ratio (PAR, see Table 5.15). Mean roll (RR) had age-related pairwise performance differences across all angles, except for the 0° angle. For movement variability (MV), and mean speed (SP) significant age-related performance differences were observed only for targets located at the right side, and at the bottom half of the screen, respectively. For pause location distance (PLD), significant pairwise performance differences between older and younger adults were observed only for the horizontal locations (0° and 180° angles). Significant interaction effect of age $\times$ angle on direction changes along all axes (DC-X, DC-Y, DC-Z) and path axis ratio (PAR) demonstrated that older adults disproportionately had higher direction change counts along the x- and the z-axis (DC-X and DC-Z)

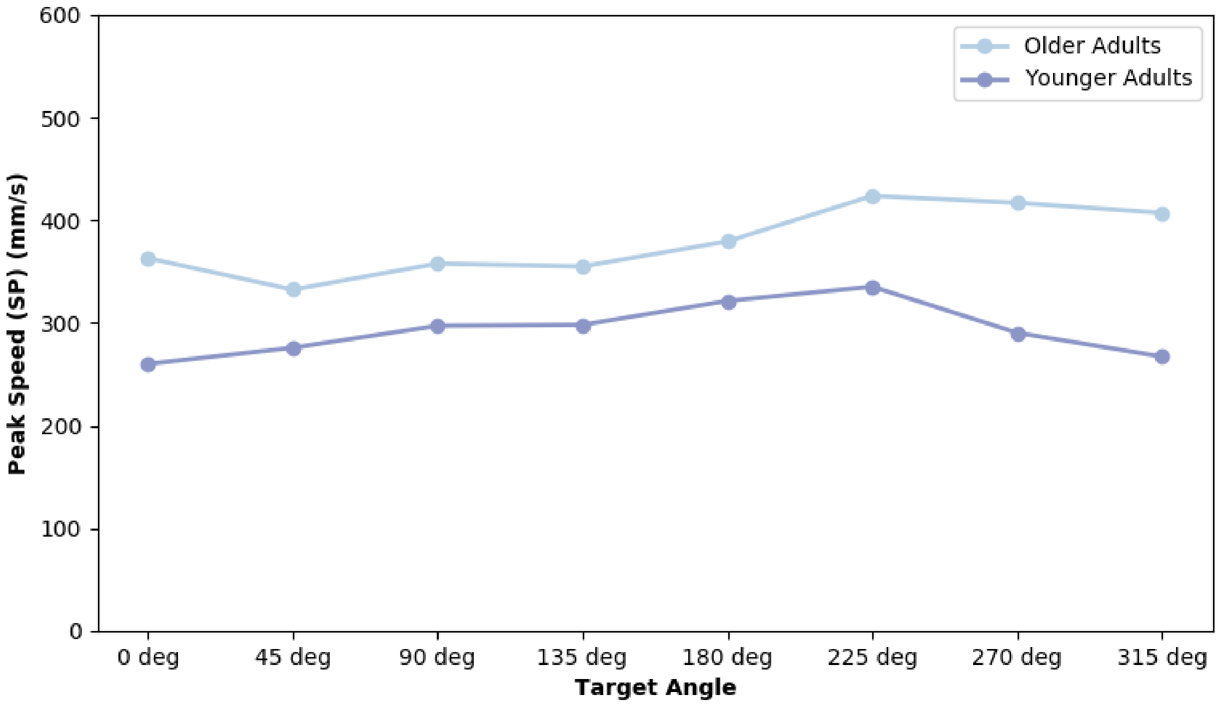


Figure 5.41 Interaction effect of age × angle on peak speed (SP). For both older and younger adults, $n = 16$.

at the bottom-right quadrant, and had higher direction change counts along the y-axis (DC-Y) and path axis ratio (PAR) at the bottom of the screen. In individual age groups, both older and younger adults had significant higher values with targets located at the left side, compared to the right side for direction changes along all axes (DC-X, DC-Y, DC-Z), movement variability (MV), and finger rolling (RR). Moreover, higher values in older adults were observed for path axis ratio (PAR) and peak speed (SP) with targets located at the bottom of the screen, compared to the targets located at top of the screen.

In summary, results from our ANOVA analysis demonstrated that older adults generally had higher values in the finger trajectory measures when targets were relatively smaller,

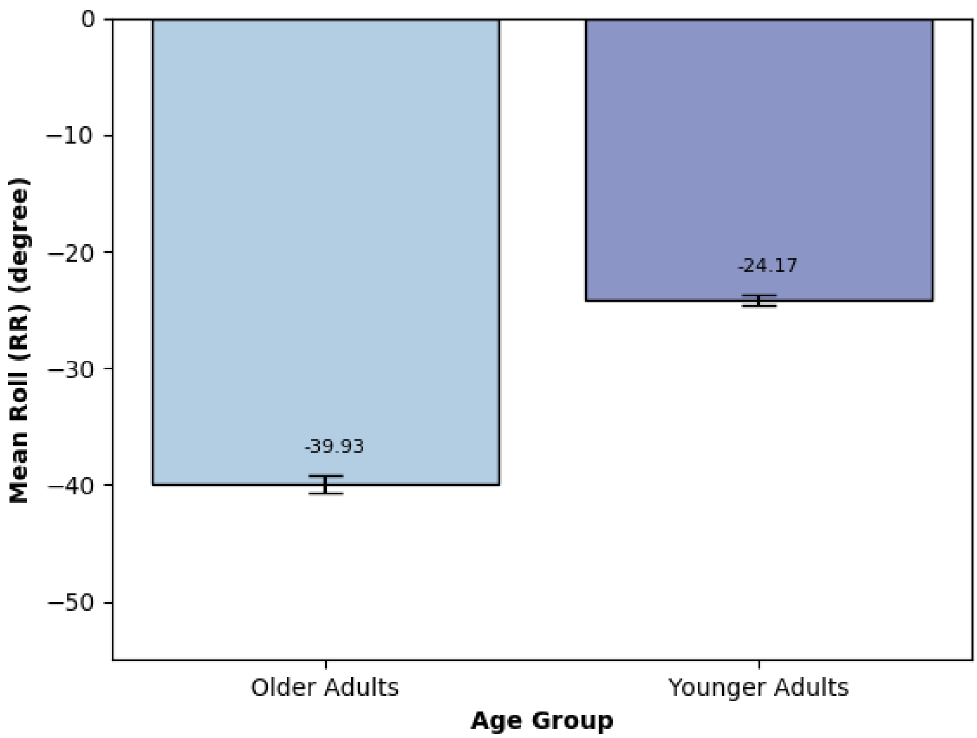


Figure 5.42 Mean roll (RR) per trial by age group. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error. All finger rotation measures are signed measures. Positive angle represents a counter clockwise rotation and negative angle represents a clockwise rotation. Rotations are with the respect to the task axis.

amplitudes were relatively larger, and targets were located at the bottom or bottom-right quadrant of the device. Overall performance analysis (i.e., movement time and error rate) of this study presented in Section 5.3.1 also reported similar age-related performance differences across target widths, amplitudes, and angles. Similar age-related performance differences evident in a subset of the finger trajectory measures add to the knowledge that differences in overall performance are more likely associated with the differences observed in these trajectory measures.

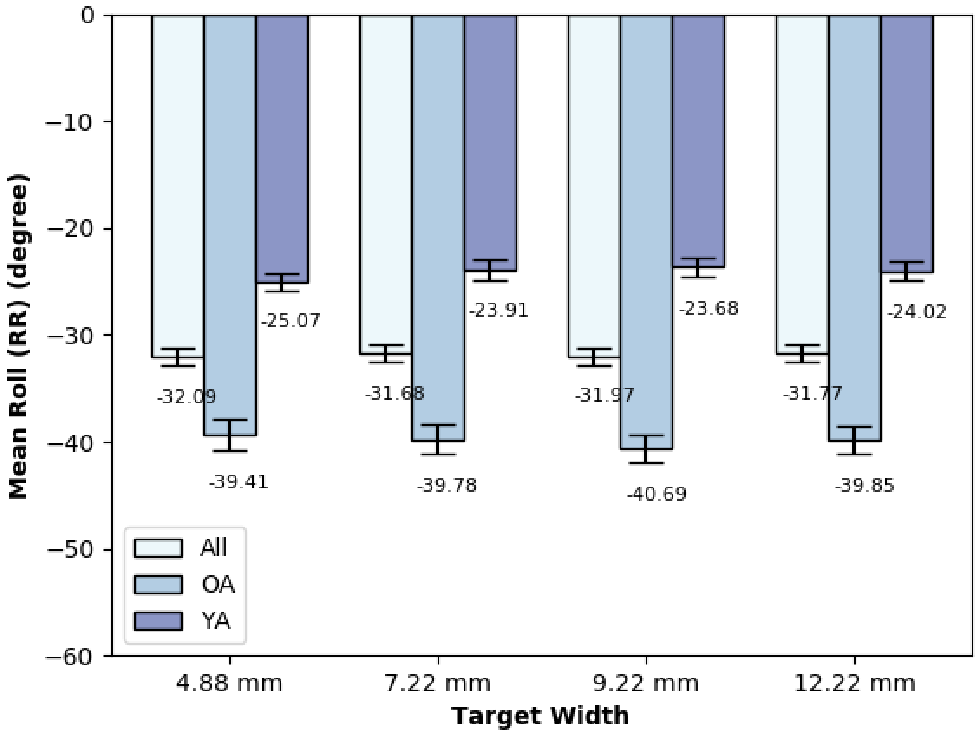


Figure 5.43 Mean roll (RR) per trial by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error. All finger rotation measures are signed measures. Positive angle represents a counter clockwise rotation and negative angle represents a clockwise rotation. Rotations are with the respect to the task axis.

5.3.3 Influence of Age on the Association between Throughput and Finger Trajectory Measures

In Section 4.4 of the previous chapter, we showed that a subset of the finger trajectory measures had significant strong relationships and dependencies with low performance throughput. Recall that we applied the finger trajectory and throughput data from combined age groups (i.e., from both older and younger adults) in those relationship and dependency analyses. Our analysis on finger trajectory measures reported significant performance differ-

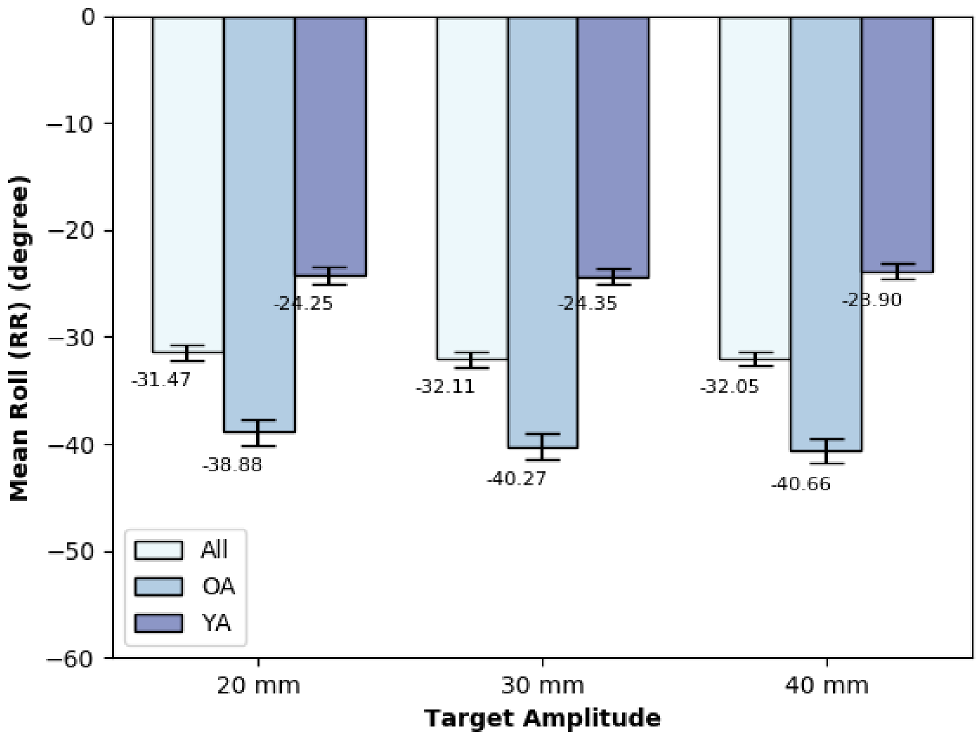


Figure 5.44 Mean roll (RR) per trial by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error. All finger rotation measures are signed measures. Positive angle represents a counter clockwise rotation and negative angle represents a clockwise rotation. Rotations are with the respect to the task axis.

ences in eight out of the sixteen finger trajectory measures, across age groups (see Section 5.3.2). Among these eight measures, four of them had significantly strong relationship with throughput in combined age groups. We also observed significant differences in performance throughput between older and younger adults (mean(SD): older adults = 2.78(0.78), younger adults = 3.61(0.86) bits/second; $p < .005$). Differences in throughput were also observed across age groups, in all twelve amplitude-width combinations (3 amplitudes × 4 widths, see Table 5.16). Age-related differences in throughput and a subset of the finger trajectory mea-

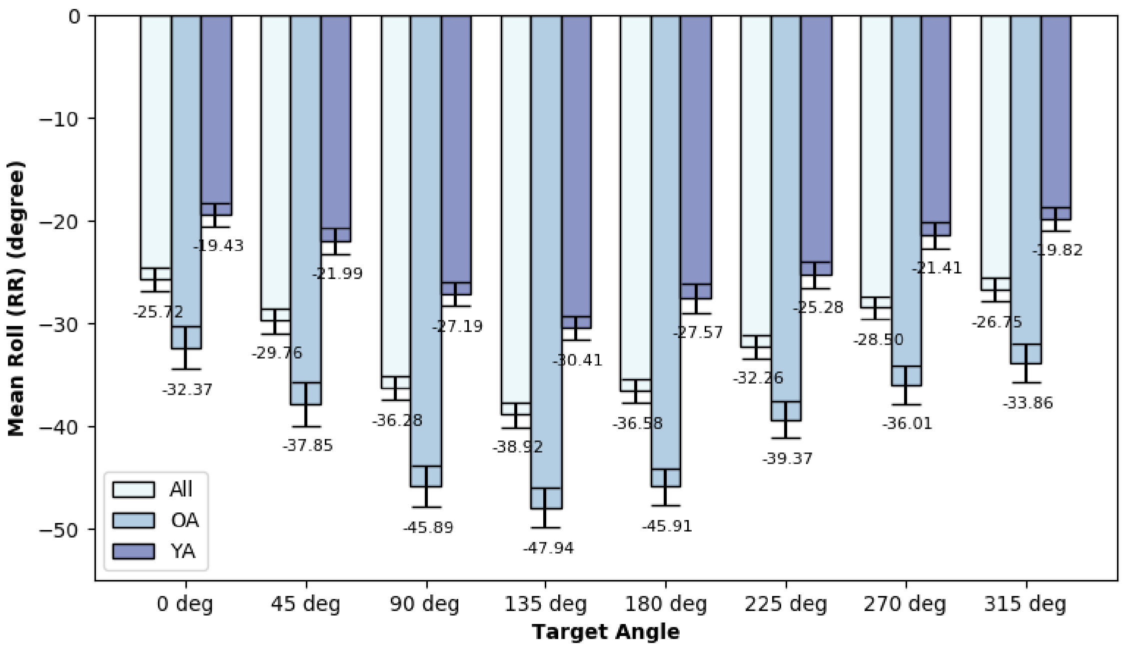


Figure 5.45 Mean roll (RR) per trial by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error. All finger rotation measures are signed measures. Positive angle represents a counter clockwise rotation and negative angle represents a clockwise rotation. Rotations are with the respect to the task axis.

Table 5.15 Pairwise performance differences across age groups by target angles. A "Y" in the cell represents presence of significant performance difference between older and younger adults, for the corresponding angle and measure.

	Target Angle (degree)							
Trajectory Measures	**0**	**45**	**90**	**135**	**180**	**225**	**270**	**315**
DC-X	Y	Y	Y	Y	Y	Y	Y	Y
DC-Y	Y	Y	Y	Y	Y	Y	Y	Y
DC-Z	Y	Y	Y	Y	Y	Y	Y	Y
MV	Y	Y	Y				Y	Y
PAR	Y	Y	Y	Y	Y	Y	Y	Y
PLD	Y				Y			
SP	Y					Y	Y	Y
RR		Y	Y	Y	Y	Y	Y	Y

sures motivated us to explore how age influenced the relationships and dependencies between the finger trajectory measures and throughput (*RQ3.2*). In the following subsections, we present our analyses to answer *RQ3.2*. We first present a partial correlation analysis (that was controlled for age) between the trajectory measures and the performance throughput, as it was reported in prior work (MacKenzie et al., 2001)[1]. This partial correlation analysis demonstrated how the age factor influenced the pairwise correlations between throughput and each of the finger trajectory measures. In the next subsections, we present the relationship and dependency analyses between throughput and all finger trajectory measures in individual age groups, similar to the analyses presented in Sections 4.4.1 and 4.4.2 for combined age groups.

Table 5.16 Performance throughput (IP) across target amplitudes and widths for older adults (OA) and younger adults (YA).

Amplitude (mm)	**Width (mm)**	**IP-OA (bits/s)**	**IP-YA (bits/s)**
20	4.88	2.82	3.72
20	7.22	2.39	3.20
20	9.22	2.15	2.84
20	12.22	1.84	2.46
30	4.88	3.31	4.26
30	7.22	2.84	3.74
30	9.22	2.56	3.38
30	12.22	2.25	3.03
40	4.88	3.54	4.46
40	7.22	3.08	3.99
40	9.22	2.81	3.65
40	12.22	2.52	3.35

[1]The partial correlation in MacKenzie et al. (2001) was controlled for input device to examine the influence of input devices on the correlations between the trajectory measures and throughput.

Partial Correlation Analysis

Partial correlations (controlled for age groups), between the finger trajectory measures and throughput are presented in Table 5.17. This table also reports the pairwise Pearsons's correlation (not controlled for age groups) from Table 4.6 of Chapter 4 for comparison. Both partial correlation ($r_{partial}$) and Pearson's correlation (r) are reported with the correlation coefficients, along with the 2-tailed significant value with $p < .05$. The strength of both types of correlations was determined with the following scale: strong ($r >= |0.50|$), moderate ($|0.30| < r < |0.50|$), and weak ($r <= |0.30|$) (Cohen, 1988). A large drop in the $r_{partial}$, compared to r indicates significant effect of age on the Pearsons's correlation (r) between that finger trajectory measure and throughput. The partial correlation coefficient $r_{partial}$ of the following measures: direction changes along all axes (DC-X, DC-Y, DC-Z), and path axis ratio (PAR) became rather weak and non-significant ($|0.09| <= r_{partial} <= |0.29|, p > .05$), although they had significantly strong Pearson's correlations (r) with throughput ($|0.58| <= r <= |0.64|, p < .005$). We also observed large drops in the moderate Pearson's correlations between throughput and movement variability (MV: $r = -0.28, r_{partial} = 0.06$) and peak speed (SP: $r = -0.31, r_{partial} = 0.02$). Such large differences in the r and $r_{partial}$ values (between 0.29 to 0.49) unpacked that the Pearson's correlations between throughput and these finger trajectory measures were significantly influenced by age. When the age factor was removed in the partial correlation analyses, their correlations with throughput became weaker. The partial correlation analysis also reported the correlations between age and the finger trajectory measures (fourth column of Table 5.17). We observed significantly moderate to strong correlations between age groups and the following eight measures: direction changes along all axes (DC-X, DC-Y, DC-Z), movement variability (MV), Pause location distance (PLD), path axis ratio (PAR), peak speed (SP), mean roll (RR). Our descriptive and inferential statistics (presented in Section 5.3.2) also reported age-related performance differences for all of these eight finger trajectory measures.

Table 5.17 Pairwise Pearson's correlation coefficient (r) and Partial correlation coefficient ($r_{partial}$) between throughput (IP) and all finger trajectory measures. The Partial correlation is controlled by age group.

Finger Trajectory Measure	Pearson's Correlations with IP (r)	Partial Correlations with IP ($r_{partial}$)	Correlations with Age Group
DC-X	-.62**	-0.24	0.67**
DC-Y	-.58**	-0.29	0.55**
DC-Z	-.64**	-0.20	0.71**
TPC	-0.26	-0.11	0.24
MV	-0.28	0.06	0.42*
MO	0.09	-0.08	-0.19
ME	-0.10	0.11	0.22
PF	-.63**	-0.63**	0.32
PD	-.50**	-0.47**	0.27
PLD	-.71**	-0.70**	0.39*
PAR	-.58**	-0.09	0.70**
SP	-0.31	0.02	0.42*
SM	0.04	0.35	0.23
RY	-0.13	-0.22	-0.02
RP	-0.17	0.03	0.24
RR	0.18	-0.15	-0.35*

**$p < .005$, *$p < .05$

Relationship Analysis in Individual Age Groups

As our partial correlation analysis confirmed that age influences the correlations between some of the finger trajectory measures and throughput, we further examined the relationships between the finger trajectory measures and throughput in individual age groups, similar to the relationship analyses that we presented in Section 4.4 for combined age groups. Relationship analyses in both age groups were conducted with pairwise correlation analyses between each of the finger trajectory measures and throughput, also between each pair of finger trajectory measures. All correlation analyses reported the Pearson's correlation coefficient (r), along with the 2-tailed significant value with $p < .05$. The strengths of correlations were determined by the following scale: strong ($r >= |0.50|$), moderate ($|0.30| <= r < |0.50|$), and weak ($r < |0.30|$) (Cohen, 1988). We also constructed relationship models from all pairwise correlations between throughput and trajectory measures, across age groups. In these relationship models (presented in Figures 5.46 and 5.47, respectively), each node represents a finger trajectory measure, and the shaded node in grey represents the performance throughput (IP). The nodes in blue represent the measures that have significantly strong correlations with throughput. The connectors represent significantly strong correlations ($r > |0.50|$, $p < .05$) between the measures represented by the nodes they connect. Moderate, weak and non-significant correlations were not shown in these models.

Relationship Analysis for Older Adults. We report the pairwise Pearson's correlations (r) between throughput and each of the finger trajectory measures for older adults in Table 5.18. Among all finger trajectory measures, pause frequency (PF), pause duration (PD), and pause location distance (PLD) had strong and significant negative correlations with performance throughput ($-0.84 <= r <= -0.62, p < .05$) for older adults. The pair-wise correlations between the remaining measures and throughput were weak to moderate, but not significant ($|0.11| <= r <= |0.39|, p > .05$). Among these remaining measures, mean speed (SM) had significantly strong negative correlations with pause frequency (PF, $r = -0.59, p < .05$) and pause duration (PD, $r = -0.56, p < .05$). We also observed moderate to strong significant correlations between some pairs of finger trajectory measures (see Table 5.18).

We present the relationship model between performance throughput and the finger trajectory measures for older adults in Figure 5.46. The relationship model for older adults had three distinct clusters of measures with strong inter-correlations between measures within the clusters, but relatively weaker inter-correlations outside the cluster:

- **Cluster 1** was consisted of the pause-related measures: pause frequency (PF), pause duration (PD), and pause location distance (PLD). These measures were the only measures to be significantly and strongly correlated to performance throughput ($-0.84 <= r <= -0.62, p < .05$, see Table 5.18). These measures also had very strong positive inter-correlations with each other ($0.88 <= r <= 0.93, p < .005$). The only significantly strong correlations observed outside the cluster was with mean speed (SM, $-0.59 <= r <= -0.56, p < .05$). Correlations between PF, PD, and PLD and the

Table 5.18 Pairwise Pearson's correlations between throughput and all finger trajectory measures, for older adults (** = $p < .005$, * = $p < .05$.)

	IP	DC-X	DC-Y	DC-Z	TPC	MV	MO	ME	PF	PD	PLD	PAR	SP	SM	RY	RP
DC-X	-0.22															
DC-Y	-0.25	0.89**														
DC-Z	-0.11	0.95**	0.80**													
TPC	-0.15	0.65**	0.48	0.50												
MV	0.14	0.12	-0.26	0.27	0.22											
MO	-0.24	-0.19	0.34	-0.05	0.43	-0.69**										
ME	0.19	-0.18	-0.40	0.03	-0.25	0.81**	-0.96**									
PF	-0.77**	-0.20	-0.10	-0.26	-0.22	-0.30	0.21	-0.24								
PD	-0.62*	-0.36	-0.24	-0.42	-0.30	-0.31	0.23	-0.26	0.93**							
PLD	-0.84**	-0.06	0.05	-0.18	0.05	-0.34	0.42	-0.39	0.92**	0.88**						
PAR	-0.01	0.82**	0.55*	0.86**	0.63**	0.52*	-0.04	0.08	-0.30	-0.37	-0.20					
SP	0.13	0.82**	0.70**	0.85**	0.51*	0.18	0.16	-0.17	-0.40	-0.42	-0.26	0.88**				
SM	0.39	0.67**	0.41	0.72**	0.55*	0.50	-0.06	0.09	-0.59*	-0.56*	-0.49	0.91**	0.87**			
RY	-0.29	-0.03	0.29	-0.01	-0.30	-0.58*	0.12	-0.27	0.31	0.14	0.23	-0.35	-0.15	-0.47		
RP	0.14	0.22	0.09	0.29	0.36	0.67**	-0.50	0.56*	-0.36	-0.43	-0.37	0.37	0.12	0.35	-0.16	
RR	-0.21	-0.10	0.15	-0.18	-0.23	-0.84**	0.65**	-0.77**	0.36	0.33	0.39	-0.33	-0.03	-0.36	0.61*	-0.76**

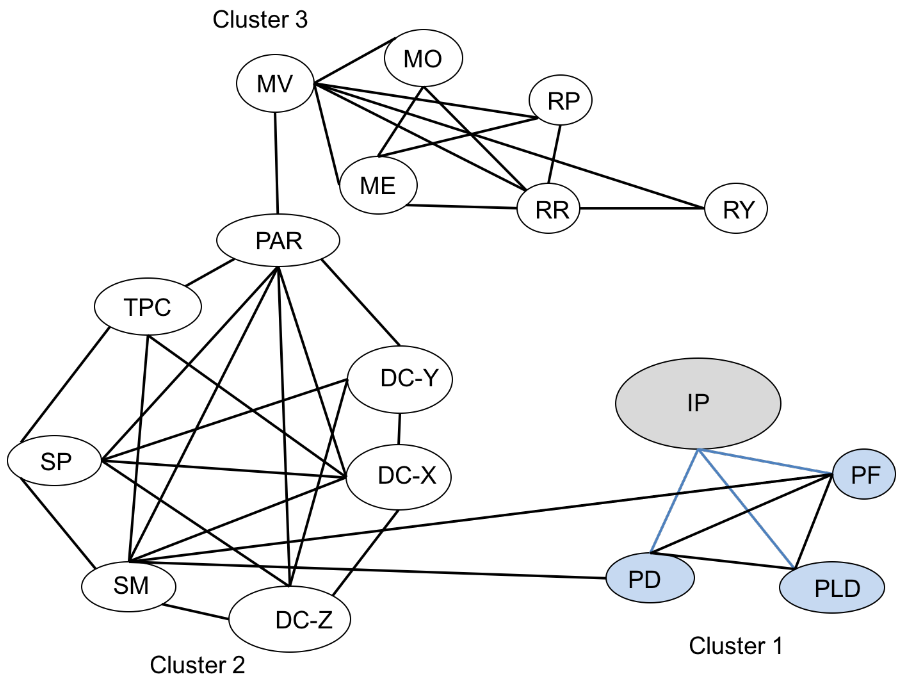


Figure 5.46 Relationship model for performance throughput (IP) and all finger trajectory measures for older adults. The shaded node represents IP, and other nodes represent finger trajectory measures. Trajectory measures having strong and significant correlations with throughput are colored in blue. The connectors represent a significantly strong correlation with $r > |0.50|, p < .05$.

remaining measures, outside this cluster, were weak to moderate, and not significant ($|0.10| <= r <= |0.42|, p > .05$).

- **Cluster 2** consisted of direction changes along all axes (DC-X, DC-Y, and DC-Z), task plane crossing (TPC), peak and mean speed (SP and SM), and path axis ratio (PAR). All of these measures had moderate to strong positive pairwise correlations with each other ($0.41 <= r <= 0.95, p < .05$, see Table 5.18). Out of the twenty-one pairwise correlations within this cluster, only three pairwise correlations were not significant (DC-Y and TPC: $r = 0.49$, DC-Y and SM: $r = 0.41$, and DC-Z and TPC

$r = 0.50$). Mean speed (SM) was the only measure to have significantly strong correlations with measures that were outside of this cluster (PF: $r = -0.59, p < .05$ and PD: $r = -0.56, p < .05$) that were also strongly correlated to throughput. These strong correlations, both inside and outside of the cluster, demonstrate that higher values in the measures from cluster 2 were indirectly associated with lower performance throughput.

- None of the measures from **Cluster 3** had any moderate or strong correlations with throughput ($r < |0.30|, p > .05$). These measures had strong inter-correlations with each other ($|0.50| <= r <= |0.96|, p < .05$). The only correlation observed outside the cluster was between movement variability (MV) and path axis ratio (PAR) from cluster 2 ($r = 0.52, p < .05$). Correlations with other measures from other clusters were weak and non-significant ($r < |0.30|, p > .05$).

The relationship model for older adults demonstrated that all finger trajectory measures were directly or indirectly related to throughput (see Figure 5.46). In Section 5.3.2, we reported eight finger trajectory measures to have significant performance differences across age groups. These measures were direction changes along all axes (DC-X, DC-Y, and DC-Z), movement variability (MV), path axis ratio (PAR), pause location distance (PLD), peak speed (SP) and mean roll (RR). If we take a closer look at the relationship model for the older adults, we can see that these finger trajectory measures also had significant direct or indirect relationships with throughput. The pause location distance was directly related to throughput ($r = -0.84, p < .005$). Direction changes along all axes, path axis ratio, and peak speed, all belonged to cluster 2, were indirectly related to throughput via mean speed (SM). All of these measures had moderate to strong positive correlations with mean speed ($0.41 <= r <= 0.91, p < .05$ for all but DC-Y). Consequently, Mean speed had strong negative correlations with pause frequency (PF: $r = -0.59, p < .05$) and pause duration (PD: $r = -0.56, p < .05$), both had strong negative correlations with throughput (PF: $r = -0.77$, PD: $r = -0.62, p < .005$ for both). Movement variability and mean roll, both from cluster 3, had indirect relationship with throughput via path axis ratio and mean speed. Movement variability had strong positive correlation with path axis ratio ($r = 0.52, p < .05$), and mean roll had strong positive correlation with movement variability ($r = 0.84, p < .005$). These direct and indirect negative relationships between throughput and these finger trajectory measures underlined that higher values in these measures influenced lower performance throughput in older adults.

Relationship Analysis for Younger Adults. The pairwise correlations between performance throughput and the finger trajectory measures for younger adults are presented in Table 5.19. For younger adults, only pause frequency (PF: $r = -0.70, p < .005$) and pause location distance (PLD: $r = -0.67, p < .005$) had significantly strong negative correlations with throughput. Correlations between the remaining finger trajectory measures and throughput were weak to moderate, but not significant ($|0.00| <= r <= |0.43|, p > .05$). None of these remaining measures, other than pause duration (PD), had indirect relationship with throughput. However, moderate to strong significant correlations between some pairs of the remaining finger trajectory measures were observed (see Table 5.19).

Table 5.19 Pairwise Pearson's correlations between throughput and all finger trajectory measures, for younger adults (** = $p < .005$, * = $p < .05$.)

	IP	DC-X	DC-Y	DC-Z	TPC	MV	MO	ME	PF	PD	PLD	PAR	SP	SM	RY	RP
DC-X	-0.33															
DC-Y	-0.43	0.92**														
DC-Z	-0.36	0.90**	0.90**													
TPC	-0.07	0.50*	0.38	0.22												
MV	-0.12	0.29	0.24	0.53*	0.02											
MO	0.15	-0.45	-0.55*	-0.71**	0.06	-0.72**										
ME	0.00	0.04	0.17	0.31	-0.18	0.73**	-0.76**									
PF	-0.70**	0.22	0.33	0.34	0.05	0.25	-0.31	0.42								
PD	-0.41	0.02	0.06	0.13	-0.23	-0.02	-0.11	0.20	0.75**							
PLD	-0.67**	0.27	0.39	0.45	0.11	0.25	-0.38	0.27	0.87**	0.67**						
PAR	-0.22	0.86**	0.77**	0.91**	0.29	0.54*	-0.63**	0.20	0.07	-0.05	0.24					
SP	-0.10	0.87**	0.85**	0.76**	0.59*	0.21	-0.48	0.20	0.29	0.09	0.29	0.67**				
SM	0.32	0.73**	0.56*	0.62**	0.45	0.18	-0.33	-0.08	-0.31	-0.28	-0.15	0.74**	0.73**			
RY	-0.20	0.00	0.25	-0.04	0.22	-0.24	-0.16	0.13	0.04	-0.10	0.08	-0.03	0.13	-0.14		
RP	-0.20	0.60*	0.49	0.65**	0.22	0.53*	-0.41	0.07	0.03	-0.12	0.22	0.80**	0.41	0.60*	-0.20	
RR	-0.08	0.09	0.26	-0.09	0.31	-0.35	0.09	0.08	0.13	0.12	-0.01	-0.17	0.29	-0.13	0.76**	-0.38

The relationship model for younger adults is presented in Figure 5.47. This model did not have similar cluster structure as the relationship model of older adults (presented in Figure 5.46), although we observed three clusters:

- **Cluster 1** was formed with the pause-related measures: pause frequency (PF), pause duration (PD), and pause location distance (PLD). These measures had very strong significant inter-correlations with each other ($0.67 <= r <= 0.87, p < .005$). Moreover, this was the only cluster to have measures with significantly strong correlations with throughput ($-0.70 <= r <= -0.67, p < .005$). No strong or moderate significant correlations were observed between these measures, and other remaining measures outside this cluster ($|0.01| <= r <= |0.45|, p > .05$ for all).

- **Cluster 2** was a large cluster formed with the following eleven measures: direction changes along all axes (DC-X, DC-Y, DC-Z), task plane crossing (TPC), path axis ratio (PAR), peak and mean speed (SP and SM), movement variability, offset and error (MV, MO, ME), and mean pitch (RP). The pairwise correlations between measures within the cluster were mostly moderate to strong and significant ($r > |0.30|, p < .05$). However, no significant correlations were observed with measures that were outside the cluster.

- **Cluster 3** was a small cluster formed with mean roll (RR) and mean yaw (RY). These two measures had significantly strong correlations with each other ($r = 0.76, p < .005$). No significant correlations outside the cluster were observed.

The relationship model for younger adults demonstrated that the pause-related measures (PF, PD and PLD) from cluster 1 were the only measures to have any direct or indirect relationship with throughput in younger adults. The remaining measures from cluster 2 and 3 did not have any association with throughput, meaning changes in any of these measures did not influence any changes in the throughput of younger adults.

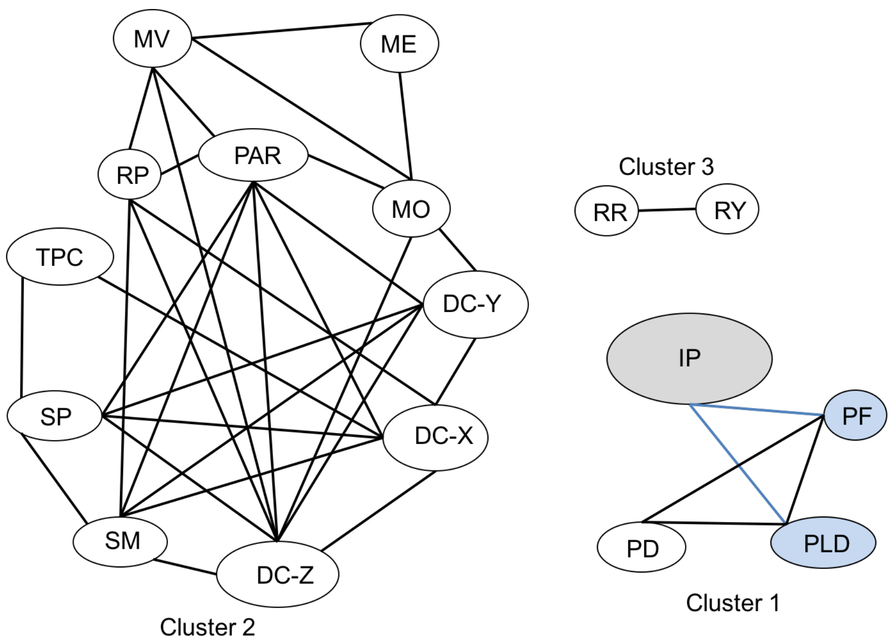


Figure 5.47 Relationship model for performance throughput (IP) and all finger trajectory measures for younger adults. The shaded node represents IP, and other nodes represent finger trajectory measures. Trajectory measures having strong and significant correlations with throughput are colored in blue. The connectors represent a significantly strong correlation with $r > |0.50|, p < .05$.

Dependency Analysis in Individual Age Groups

Similar to the relationship analysis on the combined age groups, presented in Chapter 4 (Section 4.4.1), we observed significantly strong inter-correlations among some finger trajectory measures in both age groups. These strong inter-correlations may have reflected on the combined, but not individual, contributions of these measures on throughput. To understand the independent contributions of each of the finger trajectory measures on throughput, we present similar dependency analysis in individual age groups. We followed the same procedure in these dependency analyses, as we did in Section 4.4.2. Dependency analysis was conducted with a multiple regression analysis between throughput (as the dependent variable) and all finger trajectory measures (as the independent variables) with a forward selection method. We further continued multiple steps of multiple regression analyses among the finger trajectory measures to understand how do they relate to each other. In each multiple regression analysis, we considered one measure (having the highest common variance with the dependent variable in the previous step) as the dependent variable and the remaining ones as the independent variables. For more details on the step-by-step procedure of dependency analysis, please go to Section 4.4.2. Common variances for regression analyses were reported with the coefficient of determination (r^2) for all multiple regression analyses. We considered the following scale to determine the strength of the common variance: strong ($r^2 >= 0.20$), moderate ($0.10 <= r^2 < 0.20$), and weak ($r^2 < 0.10$) (Tabachnick & Fidell, 2001). The ANOVA analyses of the final models from all multiple regression analyses were also reported. We also constructed dependency models from these step-by-step regression analyses, across age groups. In these dependency models, the node representing performance throughput (IP) is colored in grey, and nodes having significant strong independent contributions on throughput are colored in blue. The solid and dashed connectors present significantly strong ($r^2 >= 0.20$) and moderate ($0.10 <= r^2 < 0.20$) common variances, respectively. Weak dependencies are not shown in the model.

Dependency Analysis for Older Adults. The first row of Table 5.20 presents the multiple regression model for throughput in older adults. Pause location distance (PLD) had the highest independent contribution on throughput ($r^2 = 0.70$, final model: $r^2 = 0.70, F_{1,14} = 32.91, p < .0005$). Independent contributions from the remaining finger trajectory measures on throughput were weak and non-significant ($r^2 < 0.10, p > .05$). We observed that all pause-related measures, pause frequency (PF), duration (PD), and location distance (PLD) had significantly strong negative correlations with throughput in the relationship model for older adults (see Figure 5.46). The dependency analysis revealed that among these three measures, pause location distance (PLD) had the most independent contributions on throughput. Moreover, pause location distance had strong inter-dependencies with pause frequency (PF: 84% common variance with PLD) and pause duration (PD: 87% common variance with PF, see Table 5.20).

The dependency model for older adults is presented in Figure 5.48. This model mostly conforms to the cluster structure of the relationship model (see Figure 5.46). We observed stronger interdependencies among the pause-related measures from cluster 1. Mean speed (SM), from cluster 2, contributed on 32% common variance for pause duration (PD), conforming with the moderate correlations with pause duration and frequency (PD and PF) in the relationship model. Consequently, mean speed (SM) had both direct and indirect independent strong contributions (r^2 was between 0.72 to 0.89) from path axis ratio (PAR),

Table 5.20 Multiple regression analyses between performance throughput and the finger trajectory measures for older adults.

Dependent Variable	Independent Variable(s) (r^2)	Final Model
IP	PLD (0.70)	$r^2 = 0.70, F_{1,14} = 32.91, p < .0005$
PLD	PF (0.84), TPC (0.07)	$r^2 = 0.91, F_{2,13} = 63.05, p < .0005$
PF	PD (0.87)	$r^2 = 0.87, F_{1,14} = 95.20, p < .0005$
PD	SM (0.32)	$r^2 = 0.32, F_{1,14} = 6.55, p < .05$
SM	PAR (0.82)	$r2 = 0.82, F_{1,14} = 63.94, p < .0005$
PAR	SP (0.77), MV (0.14), DC-X (0.04), ME (0.03), MO (0.01)	$r^2 = 0.99, F_{5,10} = 130.51, p < .0005$
SP	DC-Z (0.72)	$r^2 = 0.72, F_{1,14} = 35.41, p < .0005$
DC-Z	DC-X (0.89), MO (0.06)	$r^2 = 0.95, F_{2,13} = 123.42, p < .0005$
DC-X	DC-Y (0.78), MV (0.14), ME (0.03), RP (0.02)	$r^2 = 0.97, F_{4,11} = 84.93, p < .0005$
DC-Y	None	
MV	RR (0.70)	$r^2 = 0.70, F_{1,14} = 33.23, p < .0005$
RR	ME (0.59), TPC (0.19), RY (0.07), RP (0.07)	$r^2 = 0.92, F_{4,11} = 30.71, p < .0005$
ME	MO (0.92), TPC (0.03), DC-Y (0.03)	$r^2 = 0.98, F_{3,12} = 162.40, p < .0005$
MO	None	
TPC	DC-X (0.43)	$r^2 = 0.43, F_{1,14} = 10.41, p < .05$

peak speed (SP), direction changes along the z-, x-, and y- axis (DC-Z, DC-X, and DC-Y), respectively, all of which were from cluster 2 of the relationship model. From the same cluster, task plane crossing (TPC) had 43% common variance with direction changes along the x-axis (DC-X). The following measures from cluster 3: mean roll (RR), movement error (ME), and movement offset (MO), respectively, had strong direct and indirect contributions (r^2 was between 0.59 to 0.92) on movement variability (MV). Moreover, MV had moderate contributions (14%) to each of path axis ratio (PAR) and direction changes along the x-axis (DC-X) from cluster 2. Our analysis did not find any moderate or strong independent contributions of mean pitch (RP) and mean yaw (RY) on any other measures, nor on the performance throughput.

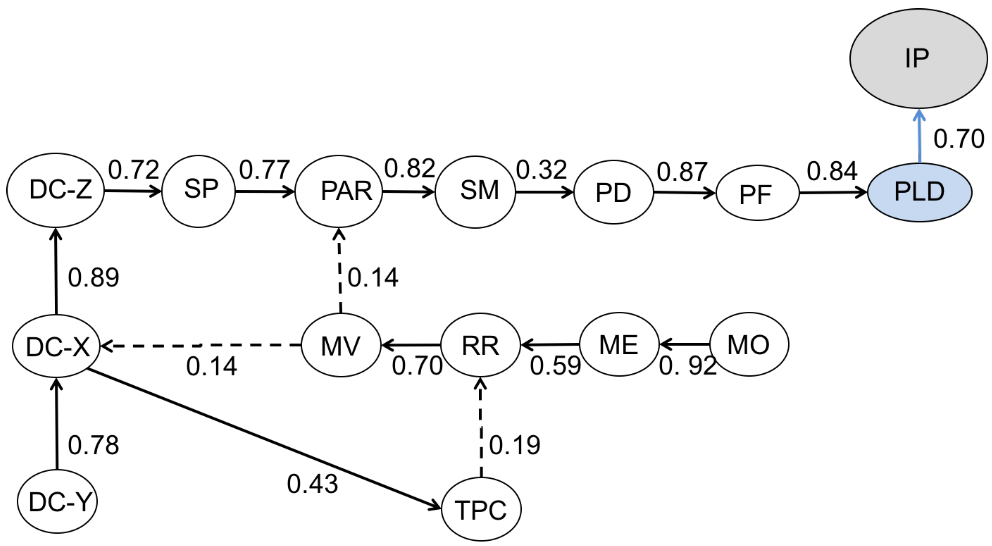


Figure 5.48 Dependency model between performance throughput and finger trajectory measures for older adults. The shaded node represents IP, and other nodes represent finger trajectory measures. Trajectory measures having strong and significant contributions on throughput are colored in blue. The solid lines represent $r^2 >= 0.20$, and the dashed lines represent $0.10 <= r^2 < 0.20$. Any variance $r^2 < 0.10$ are not shown in the model.

Throughput had direct and indirect independent contributions from all finger trajectory measures for older adults, except for mean pitch and mean yaw (see Figure 5.48). Similar to the relationship model, we observed the finger trajectory measures that had significant age-related performance differences, also had significant direct or indirect independent contributions to throughput. Among them, pause location distance had 70% common variance with throughput. This measure was also the highest independent contributor to throughput in older adults. Path axis ratio, peak speed, direction changes along the z-, x-, and y-axis had significantly strong chain of independent contributions on each other (between 72% to 89% common variance). All of these measures made indirect contributions to throughput via mean speed. Movement variability had 14% independent contribution to path axis ratio that had 82% independent contribution on mean speed. Consequently, mean roll had 70% independent contributions to movement variability. All of these results suggest that the age-related differences that we observed in these measures, also contributed to age-related differences in performance throughput.

Dependency Analysis for Younger Adults. The first row of Table 5.21 presents the multiple regression model for throughput in younger adults. The only significant independent contribution on throughput was from pause frequency (PF: $r^2 = 0.49$, final model: $r^2 = 0.49, F_{1,14} = 13.29, p < .005$). In the relationship model of younger adults, pause location distance (PLD) was the only other measure, besides pause frequency (PF), to have significant correlations with throughput (see Figure 5.47). Our next step of regression analysis demonstrated strong significant common variance between PF and PLD ($r^2 = 0.76$, see Table 5.21).

Table 5.21 Multiple regression analyses between performance throughput and the finger trajectory measures for younger adults.

Dependent Variable	Independent Variable(s) (r^2)	Final Model
IP	PF (0.49)	$r^2 = 0.49, F_{1,14} = 13.29, p < .005$
PF	PLD (0.76)	$r^2 = 0.76, F_{1,14} = 43.35, p < .0005$
PLD	PD (0.45)	$r^2 = 0.45, F_{1,14} = 11.65, p < .005$
PD	None	

The dependency model for younger adults is presented in Figure 5.49. Like the relationship model (see Figure 5.47), the dependency model also demonstrate that performance throughput for younger adults is only associated with the pause-related measures, pause frequency (PF), duration (PD), and location distance (PLD). These measures (all belonged to cluster 1 of the relationship model) also had strong interdependencies (see Figure 5.49). Pause location distance (PLD) had 76% common variance with pause frequency (PF), and pause duration (PD) had 45% common variance with pause location distance (PLD). No significant contributions from the remaining finger trajectory measures were observed on these pause-related measures. No trajectory measures other than pause frequency, duration and location directly or indirectly contributed to throughput. Conforming to the relationship model of younger adults, the dependency model suggest that changes in any of the remaining finger trajectory measures did not affect the performance throughput in younger adults.

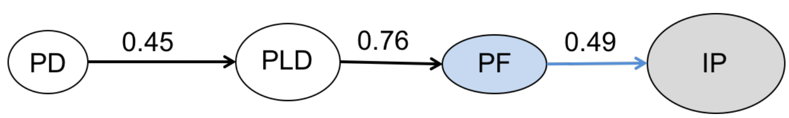


Figure 5.49 Dependency model between performance throughput and finger trajectory measures for younger adults. The shaded node represents IP, and other nodes represent finger trajectory measures. Trajectory measures having strong and significant contributions on throughput are colored in blue. The solid lines represent $r^2 >= 0.20$, and the dashed lines represent $0.10 <= r^2 < 0.20$. Any variance $r^2 < 0.10$ are not shown in the model.

5.4 Discussion

Similar to the error analysis study presented in Chapter 3, the finger trajectory analysis study demonstrated that older adults needed more movement times and generated more errors during target selection with touch interaction, which also reflected on their lower performance throughput. The detailed analysis of the selection trajectories across age groups confirmed that the finger trajectory measures that we introduced in Chapter 4 can distinguish age-related performance differences in selection tasks (*RQ3.1*). Moreover, the study results found that influence of a majority of the finger trajectory measures on the performance throughput increases with aging such that higher values in those measures contribute to lower performance throughput in older adults (*RQ3.2*).

5.4.1 Finger Trajectory Measures can Distinguish Age-related Selection Difficulties

We observed significant performance differences in the finger trajectory measures, across age groups. These results are consistent with prior works on trajectory analysis from mouse input (Hwang et al., 2005; Keates & Trewin, 2005; Wobbrock & Gajos, 2008)[2] and pen input (Ketcham et al., 2002; Sultana & Moffatt, 2013). Among the sixteen finger trajectory measures we introduced, older adults had significantly higher values in the following eight measures: direction changes along all axes, movement variability, path axis ratio, pause

[2]Both Hwang et al. (2005) and Wobbrock and Gajos (2008) compared selection performance between individuals with motor impairments and individuals with no motor impairments.

location distance, peak speed, and mean roll. Performance differences across age groups were more pronounced with smaller targets, longer amplitudes, and targets located at the bottom of the screen.

Higher counts in direction changes along all axes and higher path axis ratio indicate taking corrective submovements after an overshoot or an undershoot. Higher movement variability and path axis ratio suggest higher deviation from the task axis (i.e., the shortest path between the starting position and the target centre). Pauses in a selection trajectory indicate ending of a submovement. Therefore, higher mean pause location distance from targets implies taking a number of smaller submovements throughout the selection trajectories, in addition to taking verification pauses near the target boundaries. Higher values in the finger rolling indicate twisting the finger to correctly aim the targets. These findings suggest that while younger adults generated a primary ballistic submovement, stayed close to the task axis, and took only target verification pauses, older adults generated smaller corrective submovements as they encountered selection difficulties, such as overshoots and undershoots, higher deviation from the task axis, and pausing all along the trajectory to correct their aim. Prior studies on mouse and pen input also reported similar selection behaviour in older adults (Keates & Trewin, 2005; Ketcham & Stelmach, 2004; Smith et al., 1999).

Prior works showed higher peak speed reduced the movement time and increased the performance throughput for younger adults with no motor impairments (Ketcham et al., 2002; Wobbrock & Gajos, 2008). However, in our study, higher peak speed did not contribute to lower movement time and higher throughput for older adults. Our study results imply that sudden peak speed in older adults may have caused more erratic movements that resulted in higher deviation from the task axis and overshoots. Correcting such erratic selection behaviours also may have contributed to higher counts in direction changes, higher path axis ratio, and higher movement variability. Results from the relationship analysis for older adults support this claim as we observed significantly strong positive pairwise correlations between peak speed, and direction changes along all axes and path axis ratio. It is plausible that because of the erratic movements due to sudden peak speed, older adults required to take smaller submovements throughout the trajectory to remain close to the task axis.

5.4.2 Influences of Finger Trajectory Measures on Throughput Increases with Aging

Our relationship and dependency analyses in individual age groups showed that aging can change the dynamics between the finger trajectory measures and performance throughput. For younger adults, performance throughput had significantly strong negative relationships with only pause frequency, duration, and location distance. Moreover, these three pause-related measures were the only measures to have significant direct or indirect independent contributions to throughput. This means, changes in pause frequency, duration, and location distance were the only influential factors for any changes in the throughput in younger adults' selection tasks. On the other hand, relationships between the finger trajectory measures and throughput in older adults were not as simple as that of younger adults. Both relationship and dependency models of older adults demonstrated direct and indirect associations between throughput and almost all finger trajectory measures. Similar to younger adults, the pause-related measures: pause frequency, duration, and location distance had significantly strong direct relationships with and both direct and indirect independent contributions to throughput in older adults. In addition, the finger trajectory measures with significant age-related performance differences (i.e., direction changes along all axes, path axis ratio, movement variability, pause location distance, peak speed, and mean roll) also had significant direct or indirect relationships with and independent contributions to throughput. As we discussed in Section 5.4.1, higher values in these measures indicated that older adults had overshoots and undershoots, deviated from the task axis, and generated smaller corrective submovements throughout the trajectory. Results from the relationship and dependency analyses across age groups demonstrated that frequent occurrence of such selection behaviour among older adults reduced their overall performance throughput. These findings provided us with novel insight by identifying a subset of trajectory measures that can reflect on the potential reasons behind having low performance throughput in older adults. Future studies can emphasize on designing selection techniques that aim to reduce the values in these measures, and thus, increase the performance throughput of older adults. Further investigations on the associations between these trajectory measures and the remaining measures (that did not show age-related performance differences) may provide valuable insight on such design solutions, especially, when directly reducing these measures are not viable options.

5.4.3 Both Older and Younger Adults Pause

While prior studies on mouse input suggested that compared to younger adults, older adults have greater tendency to pause, (Keates & Trewin, 2005; Walker et al., 1997), our study did not find any performance differences in pause frequency and duration across age groups. The only age-related difference in pausing behaviour we observed was with pause location distance. Higher pause location distance in older adults implies that they paused all over the selection trajectories, whereas pauses of younger adults were concentrated near the target boundaries. Higher values in all pause-related measures (i.e., pause frequency, duration and location) were strongly associated with low performance throughput in both age groups. The relationship analyses in both age groups demonstrated significantly strong negative correlations between these pause-related measures and throughput, and significantly strong positive correlations among each other. Moreover, results from our dependency analyses revealed that pause-related measures were the strongest independent contributors to lower throughput in both age groups (i.e., pause location distance for older adults and pause frequency for younger adults).

These findings highlight pauses as a major selection behaviour in both older and younger adults that influence lower throughput with touch input. Prior studies have considered the finger occlusion problem, commonly known as the *fat finger problem*, as one of the most common selection difficulties with touch interaction (Bi et al., 2013). Various selection techniques have been developed to date to address the fat finger problem (Albinsson & Zhai, 2003; Baudisch & Chu, 2009; Benko et al., 2006; Holz & Baudisch, 2010; Olwal & Feiner, 2003; Potter et al., 1988; Ren & Moriya, 2000; Vogel & Baudisch, 2007). Although *fat finger problem* can increase the count of verification pauses that occur near the target boundary in both age groups, it is not clear how this problem can increase the pause counts all over the trajectory that we observed in older adults for all target size and in younger adults for the smallest targets. Our works presented in the previous chapter and in this chapter identified a novel, but common, selection behaviour across age groups that is strongly associated with lower throughput. It is plausible that influence of pauses on lower performance throughput remained undetected until now because no prior studies have analyzed selection trajectories from touch input before. Unavailability of a mid-air finger trajectory data collection tool may have contributed a part in that. Findings on the influence of pauses on throughput also open a new avenue of research to address selection difficulties with touch input. Future studies can focus on analyzing the spatial and temporal distribution of pauses taken by older adults, similar to the prior works on motor-impaired individuals (Hwang et al., 2005; Wobbrock & Gajos, 2008) and older adults (Ketcham et al., 2002). Future studies can also examine selection techniques to reduce pause duration, frequency, and location in both younger and older adults to improve their performance throughput.

5.5 Design Implications and Recommendations

Similar to the primary recommendations from Chapter 3, our topmost design recommendation from this study is to simply make the targets larger. Our study results showed that selection performance of older adults significantly improved when the target size was 9.22 mm or larger. Difference in error rates between age groups was not significant for the 12.22 mm targets. The error rate of older adults was reduced to 4.07% for 12.22 mm targets, very close to the acceptable 4% error rates (Soukoreff & MacKenzie, 2004). Another design recommendation from this study is to avoid placing targets at the bottom or at least at the bottom-right quadrant of the screen, as significant performance differences across age groups were evident in movement time and in a subset of the finger trajectory measures for targets at these locations. Although designing larger targets are the most obvious way to address the age-related selection difficulties, as we discussed in Section 3.5, it is not very practical given the constraints on screen real estate. For the same reason, underutilizing the screen space (i.e., placing targets only at the top-half of the screen) is not a realistic solution to improve performance, especially for touchscreen devices with smaller screens (Lee et al., 2009). A useful approach to address this challenge is to design novel techniques that can reduce the values of the finger trajectory measures that are strongly associated with lower performance throughput. We discuss some potential selection techniques inspired by prior studies and the findings from this study in the following subsection.

5.5.1 Selection Techniques to Keep Trajectory Closer to Task Axis

Our finger trajectory analysis study suggests that older adults encounter a number of overshoots and undershoots during target selection that create substantial deviation from the task axis. To recover from these erroneous movements, older adults need to take a number of smaller corrective submovements throughout the selection trajectory. These selection difficulties encountered by older adults ultimately reduce their overall performance throughput. Selection techniques that can guide older adults to stay close to the task axis might help to keep the trajectory deviation to a minimum. Techniques like *gravity well* (Hwang et al., 2003) and *haptic tunnel* (Langdon et al., 2002) that apply haptic feedback to keep the mouse cursors closer to the task axis reduced the mouse trajectory deviation for individuals with motor impairments. Similar strategies can be extended for touch input. However, designing haptic feedback for pointing tasks with touch input is challenging. Unlike mouse cursors, fingers do not keep in touch with the screen in a major portion of the finger trajectories. Alternatively, other effective touch selection and interaction techniques that are more suitable to incorporate haptic feedback can be explored. Interaction techniques like *dragging* and *steering* were reported to have lower perceived selection difficulties than *pointing* in relatively larger targets for older adults (Findlater et al., 2013). The touch selection technique *crossing* helped to reduce error rates in larger targets for individuals with motor impairments (Nicolau et al., 2014). These techniques keep fingers in-touch with the screen for the entire time, and thus, can be augmented with haptic feedback for selecting smaller targets. As an alternative approach to haptic feedback, visual feedback, for example, two-dimensional projection of the shortest paths on the screen, from the current finger location to the target location, can be introduced to assist older adults to keep close to the task axis. Guiding arrows towards the directions of the targets may also be added to the projected shortest path for further assistance. In addition, audio feedback can be introduced to extend the *haptic tunnel* for pointing tasks with touch input. An audible alert can be played, if the pointing finger moves beyond the suggested tunnel width. In both cases, motion-sensing technology is required to track the fingertip locations during the selection task. A combination of audio-visual feedback may also be applied to improve the selection trajectories, as prior work have reported that multimodal feedback is beneficial to accomplish selection tasks for older adults, over unimodal feedback, especially with small touchscreen devices (Lee et al., 2009). Other selection techniques, namely, *goal crossing* (Wobbrock & Gajos, 2008) and *angle mouse* (Wobbrock et al., 2009) have shown improvement in mouse cursor trajectory measures with motor-impaired individuals. These techniques may also be extended for touch input, and examined for older adults. The viability and effectiveness of these aforementioned techniques have to be determined before applying them to older adults, as each introduces complexity that may present new accessibility challenges.

5.6 Summary

This study evaluated the finger trajectory measures, introduced in Chapter 4, to distinguish age-related selection difficulties with touch interaction. Our study results demonstrated that, consistent to prior works in pen input, age-related performance difference was evident in a subset of these trajectory measures. In particular, older adults had significant higher counts in direction changes along all axes, movement variability, path axis ratio, pause location distance, peak speed, and mean roll. These higher values implied that older adults generated erratic finger movements due to age-related motor declines that caused a number of overshoots and undershoots, and significant deviation from the task axis. To overcome such erratic selection behaviour, older adults needed to take a number of smaller corrective submovements throughout the selection trajectory. Encountering such selection difficulties also had negative impact on the overall performance throughput of older adults. The relationship and dependency analyses across age groups unpacked that the abovementioned finger trajectory measures also had moderate to strong direct and indirect associations with lower throughput generation in older adults. Consistent to prior works in mouse and pen input, these results also confirmed that measuring the finger trajectory properties is an effective way to detect age-related selection difficulties with touch input, in addition to measuring the overall performance with movement time, error rates, and throughput. Our finger trajectory analysis provided more nuanced insight on the reasons behind selection difficulties with touch input (e.g., deviation from the task axis, overshoots and undershoots, and too many smaller corrective submovements) that are encountered by older adults. Identifying these causes of age-related selection difficulties can contribute as the initial step towards designing accessible touchscreen interfaces for older adults.

Chapter 6

Conclusions and Future Work

6.1 Thesis Summary, Contributions, and Major Findings

This thesis presents novel in-depth knowledge on age-related target selection difficulties with touch input. Prior works on age-related target selection difficulty have helped us to understand the selection difficulties encountered with mouse input, and to a lesser extent, pen input. This thesis extends this body of work to touch input. Along this process, this thesis answers three research questions (RQs) and presents three main contributions and one secondary contribution that are summarized in the following subsections.

6.1.1 Selection Error Analysis

The first main contribution made by this thesis is identifying touch selection errors that are encountered by older adults. In our error analysis study, we first provided an overview of general performance differences, observed with touch input, in terms of selection time, error rates, corrective attempts, finger pressure, and selection endpoint variability, between age groups. Then, we presented a detailed analysis of types and ranges of selection errors that are generated by older adults, extending the prior works in mouse and pen input errors (Keates & Trewin, 2005; Moffatt & McGrenere, 2007). In this study, we answered the following research questions (*RQ1*):

> *RQ1.1. What types of selection errors are encountered by older adults with touch input?*
>
> *RQ1.2. Among all types of selection errors encountered by older adults, which one is the most predominant error?*

Our error analysis study confirmed that aging influences overall performance differences in touch input. Moreover, aging introduces a wider range of selection errors in older adults. We outline the major findings from the error analysis study in the following bullet points:

- ***Overall Performance.*** Consistent with past findings, older adults required longer movement time, and generated more errors, compared to younger adults. Older adults required more corrective attempts for recovering from errors that may introduce substantial frustration in a real-life situation. Our results also demonstrated higher selection endpoint variability, and higher finger pressure at the selection endpoints in older adults. Target distance (amplitude) and size (width) had significant influences on both movement time and error rates in both age groups. The influence of target width was more pronounced on error rates, where, older adults disproportionately had very high error rates (62.4%) with the smallest (4.88 mm) targets that are roughly the size of common menu items in smartphones. We also observed variability in angular movement behavior. Movement times were higher for targets located at the bottom-right quadrant, as reported in previous studies with pen interaction (Hancock & Booth, 2004).

- ***Error Distribution.*** Older adults encountered a broader range of selection errors. Our study results concluded that while older adults encountered both miss (27.87%) and slip (4.29%) errors, younger adults hardly slipped (8.39 % miss errors and 0.79% slip errors). Miss errors were more prevalent than slip errors in both older and younger adults. The total count of miss errors were over six times higher than that of slip errors in older adults. As the targets got smaller, miss errors became even more prevalent than slip errors in older adults – being more than ten times higher than the slip errors, with the smallest targets. Both miss and slip errors had higher concentrations near the target boundaries.

- ***Input Device Specific Errors.*** Our study demonstrated that, with touch input, older adults encountered more miss errors than slip errors. Even though both pen and touch are direct forms of interaction, prior work demonstrated that slip errors are more dominating than miss errors in older adults with pen input (Moffatt & McGrenere, 2007). Differences in the properties of these input devices – i.e., finger having more friction, but less precision than a pen – are possibly the reasons behind the difference in the prominent error types across input devices.

6.1.2 Finger Trajectory Measures

As our overall performance analysis from *RQ1* provided clear indication that older adults encounter substantial selection difficulties with touch input compared to younger adults, we wanted to further investigate the selection difficulties of older adults by analyzing their selection trajectories. As the second major contribution of this thesis, we extended the two-dimensional mouse input trajectory measures from prior works (Hwang et al., 2005; Keates & Trewin, 2005; MacKenzie et al., 2001) to three-dimensional finger trajectory measures to analyze selection trajectories from touch input. We answered the following research question (*RQ2*) to examine the reliability of these new finger trajectory measures on indicating poor selection performance throughput in touch input.

> *RQ2.1. What is the relationship between each of the three-dimensional finger trajectory analysis measures and performance throughput for touch input?*
>
> *RQ2.2. How do these finger trajectory analysis measures relate to each other?*

Our study results demonstrated that significantly strong negative correlations exist between throughput and a subset of the new three-dimensional finger trajectory measures, namely, pause frequency, pause duration, pause location distance, direction change counts along all axis, and path axis ratio. Moreover, trajectory measures formed three distinct clusters, based on their strong inter-correlations with each other. We also detected 74% of common variance between throughput, and pause location distance and direction changes along z-axis combined. Strong inter-dependencies among the trajectory measures were also observed. All of these results indicate that finger trajectory measures can reflect on selection behaviour that are responsible for generating lower performance throughput.

As a secondary contribution, we developed a new finger trajectory data collection device that combined motion-sensing technologies with a commercial touchscreen tablet. This new apparatus is capable of collecting finger trajectory data that are not natively available from commercial touchscreen devices. Our literature review demonstrated that trajectory analysis studies are heavily focused on indirect input devices like mouse, where the trajectory data can be directly collected from the system logs (Hwang et al., 2005; MacKenzie et al., 2001; Wobbrock & Gajos, 2008). Prior pen trajectory analysis studies relied on the projected two-dimensional trajectories on the screen for collecting pen cursor locations from the device system logs (Ketcham et al., 2002; Moffatt & McGrenere, 2007). Our assumption is, absence of a finger movement data collection device may have created a barrier against pursuing trajectory analysis studies for touch interaction. An apparatus like the one we presented in this thesis is an important contribution to the field of HCI research that are concerned about capturing touch input trajectories.

6.1.3 Finger Trajectory Analysis

The third major contribution made by this thesis is to provide a detailed analysis of finger trajectories across age groups. Such finger trajectory analysis study for touch interaction is the first of its kind. In the finger trajectory analysis study, we identified the finger trajectory measures that can distinguish performance difference between older and younger adults. We also demonstrated the differences in the relationships and dependencies between throughput and the finger trajectory measures, across age groups. We answered the following research questions (*RQ3*) in this study:

> *RQ3.1. How can the finger trajectory analysis measures be used to characterize age-related performance differences?*
>
> *RQ3.2. How does age influence the relationships and dependencies between the finger trajectory analysis measures and performance throughput?*

Our study results detected significant performance differences across age groups in a subset of the finger trajectory measures. We also observed that the relationships and dependencies between throughput and finger trajectory measures change with aging. Major findings from the finger trajectory analysis study are outlined in the following bullet points:

- ***Age-related Performance Differences.*** We observed higher values in all sixteen finger trajectory measures in older adults, among which, the age-related performance differences were significant for the following eight measures: direction change counts along all three (x, y, and z) axes, path axis ratio, movement variability, peak speed, finger rolling, and pause location distance. These findings confirmed that older adults had higher counts of overshoots and undershoots, and higher deviation from the ideal task axis. Moreover, pausing all over the trajectory suggested that older adults generated smaller submovements, instead of generating a primary ballistic submovement (as younger adults), to reach the target. These significant differences in the trajectory measures reflect on the significant differences in overall throughput difference, across age groups.

- ***Influence of Age on Performance Throughput.*** Our analysis demonstrated that performance throughput of younger adults had significantly strong negative correlations and strong common variance with only pause frequency, duration, and location. Relationships and dependencies between throughput and the remaining trajectory measures were weak and not significant in that age group. With aging, the relationships and dependencies among throughput and the finger trajectory measures changed. Like younger adults, we observed strong relationships and dependencies between throughput and pause frequency, duration, and location in older adults. In addition, in older adults, we observed moderate direct and indirect relationships and dependencies between throughput and the finger trajectory measures that had significant performance difference across age groups. These findings highlighted that having higher counts in overshoots and undershoots, higher deviation from the task axis, and generating small corrective submovements all over the selection trajectory influences generating lower performance throughput in older adults.

- ***Influence of Widths, Amplitudes and Angles.*** Our study results demonstrated that age-related performance differences in the finger trajectory measures increased when targets were relatively smaller, were located further from the initial finger position, and were located at the bottom or bottom-right quadrant of screen. Significant performance differences across age groups, in terms of movement time and error rates, were also observed in those particular target widths, amplitudes, and angles.

- ***Larger Targets for Older Adults.*** Increasing the targets sizes from 9.22 mm (roughly the size of an icon in popular touchscreen devices) to 12.22 mm reduced the error rates in older adults from 9.11% to 4.07%. This error rates is very close to the 4% acceptable error rate threshold (MacKenzie, 1992). Our study results also demonstrated that increasing the target size to 12.22 mm eliminates the pairwise performance difference between older and younger adults ($p > .05$).

6.2 Future Work

This thesis provides novel insight on age-related selection difficulties by analyzing the selection errors and the three-dimensional finger trajectories from touch input. The findings presented by this thesis can be translated into design solutions to enhance the accessibility of handheld touchscreen devices for older adults. Some of these design recommendations were presented in Sections 3.5 and 5.5. This thesis also demonstrated that combining non-intrusive motion-sensing technologies with commercial touchscreen devices is a simple, but an effective way to collect touch input trajectory data. Combining motion-sensing technologies with commercial touchscreen devices create opportunities for a wider spectrum of future HCI research that are interested in capturing finger movement data for various purposes, for instance, evaluating three-dimensional gestures and developing novel accessible touch interaction techniques. Devices like motion-sensing touchscreen tablets open numerous possibilities for future research in accessible touch interaction for older adults, ranging from understanding their psychomotor behavior to designing ability-based touchscreen interfaces. This thesis can also be extended in other areas of research concerning touch input accessibility, for instance, understanding touch selection difficulties of individuals with motor impairments, and understanding difficulties with complex touch interaction techniques. In the following subsections, we present five research areas that can be benefited from this thesis.

6.2.1 Analysis of Psychomotor Behavior

The finger trajectory analysis study presented in this thesis reported similar pause frequency and mean pause duration per trial, across age groups. However, significant differences in the mean pause location distance implied that older adults generated smaller submovements throughout the selection trajectories, whereas, younger adults' submovements were generated near the target locations, presumably for target verification after a primary ballistic submovement. Such differences in submovement profiles between older and younger adults may also have influenced the performance differences in throughput across age groups, as pause location distance was strongly associated with throughput in both age groups. From these findings, it is clear that understanding the psychomotor behavior of older adults during touch interaction require further attention. Future research in this direction can emphasize on understanding the submovement structures, and pause location distribution of older adults, similar to the prior work on mouse interaction of individuals with motor impairments (Hwang et al., 2005). As we observed moderate to strong influence of speed and pause on throughput, we can assume that examining the relationships between velocity and submovements will gather further useful insight on their selection performance and difficulties, as it was useful in prior work on mouse interaction (Hwang et al., 2005). In-depth analysis of the spatial and temporal velocity profiles, for instance, identifying the location and time of peak speed and pauses, and identifying the distance of peak speed from the target location, are some of the additional logical next steps that can be taken for further psychomotor behavior analysis of older adults, similar to the prior works on mouse and pen interaction (Ketcham et al., 2002; Wobbrock & Gajos, 2008). Some of the trajectory measures presented in this thesis (i.e., movement error, movement offset, finger roll, pitch, and yaw) were calculated as the mean value per trial. These measures did not show any significant impact on throughput. Future studies may analyze these measures for each submovement to gather additional insight on the psychomotor behaviour of older adults.

6.2.2 Complex Tasks and Scenarios

This thesis presented age-related selection difficulties that are encountered with two-dimensional pointing tasks. Future studies can investigate age-related performance differences with more complex and realistic tasks, for example, text-entry, zooming, rotating, menu selection, and three-dimensional gestures, applying the measures from our error analysis and trajectory analysis studies. These measures may also be extended to assess selection difficulties with more complex touch interaction techniques, such as, sliding, steering, and crossing. Furthermore, these measures can work as a set of standard metrics for evaluating the performance of novel touchscreen techniques and gestures. Another area of future work of this thesis can be extending the studies to more complex scenarios. For instance, in our error analysis study, we observed that older adults face substantial difficulties with recovering from errors, when the targets are too small to select. It will be very interesting to analyze the age-related differences in error recovery strategies. Such studies will contribute to a greater extent on designing accessible touchscreen interfaces for older adults. Prior work applied supervised machine learning algorithms on pen input trajectory data to predict selection errors (Sultana & Moffatt, 2013). This prior work reported that higher counts in movement and orthogonal direction changes, task axis crossing, and pauses are the strongest predictors of selection errors with pen input. Similar error prediction models can be developed for touch input to identify the finger trajectory measures that are strongly associated with touch selection errors. In addition, future research can shift the experiment setup from controlled laboratory settings (similar to our thesis) to in-situ environments (Chapuis et al., 2007; Evans & Wobbrock, 2012; Gajos et al., 2012; Hurst et al., 2008; Montague et al., 2014). A major barrier of adopting in-situ experiment setup is to distinguish the unintended interaction from the intended ones (Brown et al., 2011; Jansen et al., 2011). Gajos et al. (2012) demonstrated that machine learning models can be built from mouse input trajectory data to identify unintended interaction in the in-situ environment. Similar machine learning models could be built from finger trajectory data to filter out unintended interaction with touch input. Quality data collected from in-situ environment could significantly contribute to obtaining realistic insight on age-related performance differences with touch input.

6.2.3 Different Form Factors

We conducted the studies presented in this thesis with handheld touchscreen smartphones and tablets that run on android platforms. Greater diversity in the experiment factors can enrich the experiment dataset for future analysis. For example, future work can extend this study to other commercially available touchscreen devices that are equipped with different operating systems (e.g., Mac OS X), screen sizes (e.g., wearables and big screen tabletops), and hardware (e.g., Microsoft Surface, touchscreen ATM machines, and touchscreen kiosks) to gain more insight on the impact of a more diverse set of target size, amplitude, and location. The two studies we presented in this thesis (i.e., error analysis study and trajectory analysis study) reported slightly different error rates with same-sized targets in the same age groups. In the error analysis study, we instructed the participants to hold the smartphone with their left hand in a portrait orientation. On the other hand, in the trajectory analysis study, we fixed the tablet in 45-degree angle on a table in a landscape orientation. However, from our study results, it is not clear whether the differences in the observed error rates between these two studies were because of differences in the screen size, screen orientation, operating systems, posture, across studies, or it is a result of something more complex. Future studies can investigate further in this issue. For example, studies can be designed to compare selection performance of older adults exploring different screen orientations (portrait vs. landscape), postures (e.g., sitting vs. standing vs. laying on a couch), device positions (handheld vs. placed on a table), and device angles (reclined on a tabletop vs. flat on a surface vs. vertically mounted on a wall). Another interesting avenue of future research can be conducting error analysis and trajectory analysis studies, similar to this thesis, comparing pen and touch input devices to find the best suitable touchscreen interaction method for older adults.

6.2.4 Application to Other Population

Older adult population is a diverse population in terms of their motor-cognitive-sensory abilities. However, the studies that we presented in this thesis recruited relatively tech-savvy active older adults who had mild age-related motor and cognitive impairments. This thesis demonstrated that even with mild age-related motor-cognitive declines and having prior experience with technology, performance difference exists between older and younger adults. It will be advantageous to extend this thesis to other older adult population, for instance, older adults with severe motor and cognitive impairments, and older adults who have no or very little prior experience with technologies. This can be very beneficial to understand the needs of this diverse population. Future studies might also benefit from trajectory analysis among older adult individuals with same throughput to differentiate among their encountered selection difficulties. In addition, this thesis can be extended to understand selection difficulties in individuals with motor impairments. Some of the trajectory analysis measures we extended in this thesis, for example, pause frequency, location and distance, and peak speed, were originally developed for mouse input to understand the selection difficulties, encountered by individuals with motor impairments (Hwang et al., 2005). However, performance analysis of pointing tasks with touch input for the same user population is still limited to movement time and error rates (Guerreiro et al., 2010; Mott et al., 2016; Nunes et al., 2016), presumably, because of the unavailability of the finger trajectory measures, and the finger movement tracking devices. Future studies can apply the finger trajectory measures from this thesis to explore the touch selection difficulties of individuals with motor impairments.

6.2.5 Ability-based Design

Modern handheld touchscreen devices, such as, smartphones and tablets are equipped with assistive features to accommodate audio-visual-motor impairments that can be very useful for older adults. However, recent studies showed that adoption of these built-in features are substantially lower in older adults, compared to younger adults with no impairments

(Franz et al., 2019; Wu et al., 2020). Older adults are mostly unaware of those assistive features, or encounter difficulties with configuring the best-suited features for them from a wide range of possibilities, or the available features do not accommodate their specific needs. It is also often difficult for them to remember the suitable configurations for future use. Some older adults are not keen on adopting assistive features, because they do not consider themselves as someone who needs assistance. Another reason for low adoption of these built-in features is that many older adults are either unaware of their needs for assistance, or are unaware about the changes in their needs, as motor functionalities of older adults continuously change over time (Franz et al., 2019). Ability-based design (Gajos et al., 2010; Goel et al., 2012; Wobbrock, 2019; Wobbrock et al., 2011) – that emphasizes individual's abilities, but not limitations, to offer assistance – can be a good approach towards designing accessible touchscreen interfaces for older adults (Wu et al., 2020). Adaptive user interfaces that can auto-configure themselves based on user-specific and session-specific performance data have proven to improve overall user performance of individuals with and without any motor impairment (Hurst et al., 2013; Kolly et al., 2012; Mott & Wobbrock, 2019; Trewin, 2003). Similar interface designs can also be beneficial for older adults (who are facing different magnitudes of age-related motor-cognitive-sensory declines) than providing them with built-in assistive features only. As we mentioned before, older adults are a diverse group of people in terms of their motor functionalities. Analysis of movement time, error characteristics, and finger trajectories in both individual and subgroup level can offer new research directions for ability-based adaptive user interfaces that are tailored to their diverse needs. Findings from our trajectory analysis study suggest that the finger trajectory measures can provide valuable insight on the real-time selection performance, which can be useful to detect the most-suitable configuration for the adaptive user interfaces. In addition, data from encountered errors, error categories, and finger trajectory measures from prior interaction can be included in the training sets for developing machine learning models for ability-specific user interfaces. Another future research direction this thesis can offer is to develop more nuanced performance analysis scales to categorize touch selection performance, where individual or group-level performance can be directly mapped to those scales to pinpoint the specific selection difficulties that the user is experiencing. Ability-based interface can use these scales before offering further assistance. These future research directions on ability-based design not only will improve the accessibility of touchscreen devices for older adults, but also will help individuals with permanent and situational motor impairments.

6.3 Conclusions

Age-related motor declines can introduce different types of target selection difficulties in older adults that can hinder their user experience with modern handheld touchscreen devices (e.g., smartphones and tablets). Consequently, these difficulties can cause significant disparity between older and younger adults, in terms of touchscreen technology use and adoption. In this thesis, we took an exploratory approach to understand the nature of selection difficulties with touch input that are specifically encountered by older adults. Our studies demonstrated that older adults required longer time to select targets, encountered both miss and slip errors, required more corrective attempts to recover from an error, generated higher number of overshoots and undershoots, had substantially higher deviation from the task axis, and generated a number of smaller corrective submovements to reach the targets. These age-related selection difficulties were more pronounced when the targets were smaller, distantly located, and placed at the bottom or bottom-right quadrant of the screen. Based on these findings, we outlined potential design recommendations for accessible touchscreen interfaces for older adults. We also highlighted some findings of this thesis that could benefit future research. The novel insight we gathered from this thesis will contribute to closing the digital divide across age groups.

Bibliography

Accot, J., & Zhai, S. (1997). Beyond fitts' law: Models for trajectory-based hci tasks. *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems*, 295–302. https://doi.org/10.1145/258549.258760

Accot, J., & Zhai, S. (2003). Refining fitts' law models for bivariate pointing. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 193–200. https://doi.org/10.1145/642611.642646

Alam, M. R., Reaz, M. B. I., & Ali, M. A. M. (2012). A review of smart homes—past, present, and future. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, *42*(6), 1190–1203.

Albinsson, P.-A., & Zhai, S. (2003). High precision touch screen interaction. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 105–112. https://doi.org/10.1145/642611.642631

Anderson, M., & Perrin, A. (2019). Tech adoption climbs among older adults [Retrieved: March 07, 2020]. https://www.pewresearch.org/internet/2017/05/17/tech-adoption-climbs-among-older-adults/

Atsuo, M., & Iwase, H. (2002). Empirical study on improvement of usability for touch-panel for elderly-comparison of usability between touch-panel and mouse. *IEEE International Conference on Systems Man and Cybernetics*, *1*, MA1I4–MA1I4.

Bacim, F., Nabiyouni, M., & Bowman, D. A. (2014). Slice-n-swipe: A free-hand gesture user interface for 3d point cloud annotation. *2014 IEEE Symposium on 3D User Interfaces (3DUI)*, 185–186. https://doi.org/10.1109/3DUI.2014.6798882

Bashore, T. R., Osman, A., & Heffley III, E. F. (1989). Mental slowing in elderly persons: A cognitive psychophysiological analysis. *Psychology and aging*, *4*(2), 235.

Bassily, D., Georgoulas, C., Guettler, J., Linner, T., & Bock, T. (2014). Intuitive and adaptive robotic arm manipulation using the leap motion controller. *ISR/Robotik 2014; 41st International Symposium on Robotics*, 1–7. https://ieeexplore.ieee.org/abstract/document/6840112

Baudisch, P., & Chu, G. (2009). Back-of-device interaction allows creating very small touch devices. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1923–1932. https://doi.org/10.1145/1518701.1518995

Benko, H., Wilson, A. D., & Baudisch, P. (2006). Precise selection techniques for multi-touch screens. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1263–1272. https://doi.org/10.1145/1124772.1124963

Bhuiyan, M., & Picking, R. (2011). A gesture controlled user interface for inclusive design and evaluative study of its usability. *Journal of software engineering and applications*, *4*(09), 513.

Bi, X., Li, Y., & Zhai, S. (2013). Ffitts law: Modeling finger touch with fitts' law. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1363–1372. https://doi.org/10.1145/2470654.2466180

Brown, B., Reeves, S., & Sherwood, S. (2011). Into the wild: Challenges and opportunities for field trial methods. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1657–1666. https://doi.org/10.1145/1978942.1979185

Cabreira, A. T., & Hwang, F. (2018). Evaluating the effects of feedback type on older adults' performance in mid-air pointing and target selection. *Proceedings of the Symposium on Spatial User Interaction*, 111–119. https://doi.org/10.1145/3267782.3267933

Card, S. K., English, W. K., & Burr, B. J. (1978). Evaluation of mouse, rate-controlled isometric joystick, step keys, and text keys for text selection on a crt. *Ergonomics*, *21*(8), 601–613.

Carreira, M., Ting, K. L. H., Csobanka, P., & Gonçalves, D. (2017). Evaluation of in-air hand gestures interaction for older people. *Universal Access in the Information Society*, *16*(3), 561–580.

Cash, M. (2003). Assistive technology and people with dementia. *Reviews in Clinical Gerontology*, *13*(04), 313–319.

Chaparro, A., Bohan, M., Fernandez, J., Choi, S. D., & Kattel, B. (1999). The impact of age on computer input device use: Psychophysical and physiological measures. *International Journal of Industrial Ergonomics*, *24*(5), 503–513.

Chaparro, A., Rogers, M., Fernandez, J., Bohan, M., Sang Dae, C., & Stumpfhauser, L. (2000). Range of motion of the wrist: Implications for designing computer input devices for the elderly. *Disability and rehabilitation*, *22*(13-14), 633–637.

Chapuis, O., Blanch, R., & Beaudouin-Lafon, M. (2007). *Fitts' Law in the Wild: A Field Study of Aimed Movements* (tech. rep.) [LRI Technical Repport Number 1480, Univ. Paris-Sud, 11 pages.]. https://hal.archives-ouvertes.fr/hal-00612026

Charness, N., Holley, P., Feddon, J., & Jastrzembski, T. (2004). Light pen use and practice minimize age and hand performance differences in pointing tasks. *Human Factors*, *46*(3), 373–384.

Cockburn, A., Ahlström, D., & Gutwin, C. (2012). Understanding performance in touch selections: Tap, drag and radial pointing drag with finger, stylus and mouse. *International Journal of Human-Computer Studies*, *70*(3), 218–233.

Cohen, J. (1988). Statistical power analysis jbr the behavioral. *Sciences. Hillsdale (NJ): Lawrence Erlbaum Associates*, 18–74.

Crossman, E., & Goodeve, P. (1983). Feedback control of hand-movement and fitts' law. *The Quarterly Journal of Experimental Psychology*, *35*(2), 251–278.

Dickinson, A., & Hill, R. L. (2007). Keeping in touch: Talking to older people about computers and communication. *Educational Gerontology*, *33*(8), 613–630.

Evans, A., & Wobbrock, J. (2012). Taming wild behavior: The input observer for obtaining text entry and mouse pointing measures from everyday computer use. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1947–1956. https://doi.org/10.1145/2207676.2208338

Findlater, L., Froehlich, J. E., Fattal, K., Wobbrock, J. O., & Dastyar, T. (2013). Age-related differences in performance with touchscreens compared to traditional mouse input. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 343–346. https://doi.org/10.1145/2470654.2470703

Findlater, L., & McGrenere, J. (2010). Beyond performance: Feature awareness in personalized interfaces. *International Journal of Human-Computer Studies*, *68*(3), 121–137. https://doi.org/https://doi.org/10.1016/j.ijhcs.2009.10.002

Findlater, L., & Zhang, L. (2020). Input accessibility: A large dataset and summary analysis of age, motor ability and input performance. *The 22nd International ACM SIGACCESS Conference on Computers and Accessibility*. https://doi.org/10.1145/3373625.3417031

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology*, *47*(6), 381.

Forlines, C., Wigdor, D., Shen, C., & Balakrishnan, R. (2007). Direct-touch vs. mouse input for tabletop displays. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 647–656. https://doi.org/10.1145/1240624.1240726

Franz, R. L., Wobbrock, J. O., Cheng, Y., & Findlater, L. (2019). Perception and adoption of mobile accessibility features by older adults experiencing ability changes. *The 21st International ACM SIGACCESS Conference on Computers and Accessibility*, 267–278. https://doi.org/10.1145/3308561.3353780

Gajos, K., Reinecke, K., & Herrmann, C. (2012). Accurate measurements of pointing performance from in situ observations. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 3157–3166. https://doi.org/10.1145/2207676.2208733

Gajos, K. Z., Weld, D. S., & Wobbrock, J. O. (2010). Automatically generating personalized user interfaces with supple. *Artificial Intelligence*, *174*(12), 910–950.

Gao, Q., & Sun, Q. (2015). Examining the usability of touch screen gestures for older and younger adults. *Human factors*, *57*(5), 835–863.

Goel, M., Findlater, L., & Wobbrock, J. (2012). Walktype: Using accelerometer data to accomodate situational impairments in mobile touch screen text entry. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2687–2696. https://doi.org/10.1145/2207676.2208662

Grossman, T., & Balakrishnan, R. (2005a). The bubble cursor: Enhancing target acquisition by dynamic resizing of the cursor's activation area. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 281–290.

Grossman, T., & Balakrishnan, R. (2005b). A probabilistic approach to modeling two-dimensional pointing. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *12*(3), 435–459.

Guerreiro, T., Nicolau, H., Jorge, J., & Gonçalves, D. (2010). Towards accessible touch interfaces. *Proceedings of the 12th International ACM SIGACCESS Conference on Computers and Accessibility*, 19–26. https://doi.org/10.1145/1878803.1878809

Guerrero-Rincon, C., Uribe-Quevedo, A., Leon-Rodriguez, H., & Park, J.-O. (2013). Hand-based tracking animatronics interaction. *IEEE ISR 2013*, 1–3.

Hancock, M. S., & Booth, K. S. (2004). Improving menu placement strategies for pen input. *Proceedings of Graphics Interface 2004*, 221–230.

Holz, C., & Baudisch, P. (2010). The generalized perceived input point model and how to double touch accuracy by extracting fingerprints. *Proceedings of the SIGCHI Confer-*

ence on Human Factors in Computing Systems, 581–590. https://doi.org/10.1145/1753326.1753413

Holz, C., & Baudisch, P. (2011). Understanding touch. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2501–2510. https://doi.org/10.1145/1978942.1979308

Hourcade, J. P., & Berkel, T. R. (2007). Simple pen interaction performance of young and older adults using handheld computers. *Interacting with Computers*, *20*(1), 166–183.

Huang, J., & Rai, R. (2018). Conceptual three-dimensional modeling using intuitive gesture-based midair three-dimensional sketching technique. *Journal of Computing and Information Science in Engineering*, *18*(4), 041014.

Hurst, A., Hudson, S. E., Mankoff, J., & Trewin, S. (2013). Distinguishing users by pointing performance in laboratory and real-world tasks. *ACM Trans. Access. Comput.*, *5*(2). https://doi.org/10.1145/2517039

Hurst, A., Mankoff, J., & Hudson, S. E. (2008). Understanding pointing problems in real world computing environments. *Proceedings of the 10th International ACM SIGACCESS Conference on Computers and Accessibility*, 43–50. https://doi.org/10.1145/1414471.1414481

Hwang, F., Keates, S., Langdon, P., & Clarkson, J. (2005). A submovement analysis of cursor trajectories. *Behaviour & Information Technology*, *24*(3), 205–217.

Hwang, F., Keates, S., Langdon, P., & Clarkson, P. J. (2003). Multiple haptic targets for motion-impaired computer users. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 41–48. https://doi.org/10.1145/642611.642620

Jailungka, P., & Charoenseang, S. (2018). Intuitive 3d model prototyping with leap motion and microsoft hololens. *International Conference on Human-Computer Interaction*, 269–284. https://doi.org/https://doi.org/10.1007/978-3-319-91250-9_21

Jansen, A., Findlater, L., & Wobbrock, J. O. (2011). From the lab to the world: Lessons from extending a pointing technique for real-world use. *CHI '11 Extended Abstracts* *on Human Factors in Computing Systems*, 1867–1872. https://doi.org/10.1145/1979742.1979888

Keates, S., & Trewin, S. (2005). Effect of age and parkinson's disease on cursor positioning using a mouse. *Proceedings of the 7th International ACM SIGACCESS Conference on Computers and Accessibility*, 68–75. https://doi.org/10.1145/1090785.1090800

Keates, S., Trewin, S., & Paradise, J. (2005). Using pointing devices: Quantifying differences across user groups. *Proceedings of the of 3rd International Conference on Universal Access in Human-Computer Interaction*. https://gala.gre.ac.uk/id/eprint/12736/

Keele, S. W. (1968). Movement control in skilled motor performance. *Psychological bulletin*, *70*(6p1), 387. https://doi.org/10.1037/h0026739

Ketcham, C. J., Seidler, R. D., Van Gemmert, A. W., & Stelmach, G. E. (2002). Age-related kinematic differences as influenced by task difficulty, target size, and movement amplitude. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *57*(1), P54–P64.

Ketcham, C. J., & Stelmach, G. E. (2004). Movement control in the older adult. In R. W. Pew, S. B. Van Hemel et al. (Eds.), *Technology for adaptive aging*. National Academies Press Washington, DC. https://www.ncbi.nlm.nih.gov/books/NBK97342/

Kim, S.-H., Zhang, K., McGrenere, J., Booth, K. S., & Jacova, C. (2020). A comparison of touchscreen and mouse for real-world and abstract tasks with older adults. *ACM Trans. Access. Comput.*, *13*(4). https://doi.org/10.1145/3418057

Kolly, S. M., Wattenhofer, R., & Welten, S. (2012). A personal touch: Recognizing users based on touch screen behavior. *Proceedings of the Third International Workshop on Sensing Applications on Mobile Phones*, 1.

Langdon, P., Hwang, F., Keates, S., Clarkson, P. J., & Robinson, P. (2002). Investigating haptic assistive interfaces for motion-impaired users: Force-channels and competitive attractive-basins. *Proceedings of Eurohaptics*, *2*, 122–127.

Lee, J.-H., Poliakoff, E., & Spence, C. (2009). The effect of multimodal feedback presented via a touch screen on the performance of older adults. *International conference on haptic and audio interaction design*, 128–135.

MacKenzie, I. S. (1992). Fitts' law as a research and design tool in human-computer interaction. *Hum.-Comput. Interact.*, *7*(1), 91–139. https://doi.org/10.1207/s15327051hci0701_3

MacKenzie, I. S., & Buxton, W. (1992). Extending fitts' law to two-dimensional tasks. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 219–226. https://doi.org/10.1145/142750.142794

MacKenzie, I. S., Kauppinen, T., & Silfverberg, M. (2001). Accuracy measures for evaluating computer pointing devices. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 9–16. https://doi.org/10.1145/365024.365028

Manawadu, U. E., Kamezaki, M., Ishikawa, M., Kawano, T., & Sugano, S. (2001). A hand gesture based driver-vehicle interface to control lateral and longitudinal motions of an autonomous vehicle. *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 001785–001790.

Mapari, R. B., & Kharat, G. (2016). American static signs recognition using leap motion sensor. *Proceedings of the Second International Conference on Information and Communication Technology for Competitive Strategies*, 1–5.

Marin, G., Dominio, F., & Zanuttigh, P. (2014). Hand gesture recognition with leap motion and kinect devices. *2014 IEEE International conference on image processing (ICIP)*, 1565–1569.

Massimi, M., Baecker, R. M., & Wu, M. (2007). Using participatory activities with seniors to critique, build, and evaluate mobile phones. *Proceedings of the 9th International ACM SIGACCESS Conference on Computers and Accessibility*, 155–162. https://doi.org/10.1145/1296843.1296871

McCreadie, C., & Tinker, A. (2005). The acceptability of assistive technology to older people. *Ageing and Society*, *25*(01), 91–110.

McGuffin, M., & Balakrishnan, R. (2002). Acquisition of expanding targets. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 57–64. https://doi.org/10.1145/503376.503388

Meyer, D. E., Abrams, R. A., Kornblum, S., Wright, C. E., & Keith Smith, J. (1988). Optimality in human motor performance: Ideal control of rapid aimed movements. *Psychological review*, *95*(3), 340–370.

Mikels, J. A., & Reed, A. E. (2009). Monetary losses do not loom large in later life: Age differences in the framing effect. *J Gerontol B Psychol Sci Soc Sci*, *64*(4), 457–60. https://doi.org/10.1093/geronb/gbp043

Mithal, A. K., & Douglas, S. A. (1996). Differences in movement microstructure of the mouse and the finger-controlled isometric joystick. *Proceedings of the SIGCHI conference on Human factors in computing systems*, 300–307. http://www.cs.uoregon.edu/research/ISL/research/papers/akm/

Moffatt, K., David, J., & Baecker, R. M. (2013). Connecting grandparents and grandchildren. In C. Neustaedter, S. Harrison, & A. Sellen (Eds.), *Connecting families: The impact of new communication technologies on domestic life* (pp. 173–193). Springer. https://doi.org/10.1007/978-1-4471-4192-1_10

Moffatt, K., Findlater, L., Davies, R., & McGrenere, J. (2003). Participatory design with aphasic individuals. *Extended Abstracts of Graphics Interface (GI'03).*

Moffatt, K., & McGrenere, J. (2010). Steadied-bubbles: Combining techniques to address pen-based pointing errors for younger and older adults. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1125–1134. https://doi.org/10.1145/1753326.1753495

Moffatt, K. A., & McGrenere, J. (2007). Slipping and drifting: Using older users to uncover pen-based target acquisition difficulties. *Proceedings of the 9th International ACM*

SIGACCESS Conference on Computers and Accessibility, 11–18. https://doi.org/10.1145/1296843.1296848

Montague, K., Nicolau, H., & Hanson, V. L. (2014). Motor-impaired touchscreen interactions in the wild. *Proceedings of the 16th International ACM SIGACCESS Conference on Computers and Accessibility*, 123–130. https://doi.org/10.1145/2661334.2661362

Mott, M. E., Vatavu, R.-D., Kane, S. K., & Wobbrock, J. O. (2016). Smart touch: Improving touch accuracy for people with motor impairments with template matching. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 1934–1946. https://doi.org/10.1145/2858036.2858390

Mott, M. E., & Wobbrock, J. O. (2019). Cluster touch: Improving touch accuracy on smartphones for people with motor and situational impairments. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3290605.3300257

Motti, L. G., Vigouroux, N., & Gorce, P. (2013). Interaction techniques for older adults using touchscreen devices: A literature review. *Proceedings of the 25th Conference on l'Interaction Homme-Machine*, 125–134. https://doi.org/10.1145/2534903.2534920

Murata, A., & Iwase, H. (2005). Usability of touch-panel interfaces for older adults. *Human factors*, *47*(4), 767–776.

Nazemi, K., Burkhardt, D., Stab, C., Breyer, M., Wichert, R., & Fellner, D. W. (2011). Natural gesture interaction with accelerometer-based devices in ambient assisted environments. In R. Wichert & E. Birgid (Eds.), *Ambient assisted living* (pp. 75–90). Springer. https://doi.org/https://doi.org/10.1007/978-3-642-18167-2_6

Nicolau, H., Guerreiro, T., Jorge, J., & Gonçalves, D. (2014). Mobile touchscreen user interfaces: Bridging the gap between motor-impaired and able-bodied users. *Universal access in the information society*, *13*(3), 303–313.

Nischelwitzer, A., Pintoffl, K., Loss, C., & Holzinger, A. (2007). *Design and development of a mobile medical application for the management of chronic diseases: Methods of improved data input for older people*. Springer.

Nunes, F., Silva, P. A., Cevada, J., Barros, A. C., & Teixeira, L. (2016). User interface design guidelines for smartphone applications for people with parkinson's disease. *Universal Access in the Information Society*, *15*(4), 659–679.

Olwal, A., & Feiner, S. (2003). Rubbing the fisheye: Precise touch-screen interaction with gestures and fisheye views. *In Conf. Supp. of UIST'03*, 83–84.

Paradise, J., Trewin, S., & Keates, S. (2005). Using pointing devices: Difficulties encountered and strategies employed.

Potter, L. E., Araullo, J., & Carter, L. (2013). The leap motion controller: A view on sign language. *Proceedings of the 25th Australian Computer-Human Interaction Conference: Augmentation, Application, Innovation, Collaboration*, 175–178. https://doi.org/10.1145/2541016.2541072

Potter, R. L., Weldon, L. J., & Shneiderman, B. (1988). Improving the accuracy of touch screens: An experimental evaluation of three strategies. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 27–32. https://doi.org/10.1145/57167.57171

Ramani, K. (2015). A gesture-free geometric approach for mid-air expression of design intent in 3d virtual pottery. *Computer-Aided Design*, *69*, 11–24.

Rautaray, S. S., & Agrawal, A. (2015). Vision based hand gesture recognition for human computer interaction: A survey. *Artificial intelligence review*, *43*(1), 1–54.

Ren, X., & Moriya, S. (2000). Improving selection performance on pen-based systems: A study of pen-based interaction for selection tasks. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *7*(3), 384–416.

Riviere, C. N., & Thakor, N. V. (1996). Effects of age and disability on tracking tasks with a computer mouse: Accuracy and linearity. *Journal of Rehabilitation Research and Development*, *33*, 6–15.

Robinson, L., Brittain, K., Lindsay, S., Jackson, D., & Olivier, P. (2009). Keeping in touch everyday (kite) project: Developing assistive technologies with people with dementia and their carers to promote independence. *International Psychogeriatrics*, *21*(03), 494–502.

Rogers, W. A., Fisk, A. D., McLaughlin, A. C., & Pak, R. (2005). Touch a screen or turn a knob: Choosing the best device for the job. *Human Factors*, *47*(2), 271–288.

Rosenbaum, D. A. (2009). *Human motor control*. Academic Press.

Salthouse, T. A. (1988). Cognitive aspects of motor functioning. *Annals of the New York Academy of Sciences*, *515*(1), 33–41.

Sasangohar, F., MacKenzie, I. S., & Scott, S. D. (2009). Evaluation of mouse and touch input for a tabletop display using fitts' reciprocal tapping task. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *53*(12), 839–843. https://doi.org/10.1177/154193120905301216

Schaie, K. W. (2004). Cognitive aging. In R. W. Pew, S. B. Van Hemel et al. (Eds.), *Technology for adaptive aging*. National Academies Press Washington, DC.

Schieber, F. (2003). Human factors and aging: Identifying and compensating for age-related deficits in sensory and cognitive function. *Impact of technology on successful aging*, 42–84.

Schmidt, R. A., Zelaznik, H., Hawkins, B., Frank, J. S., & Quinn Jr, J. T. (1979). Motor-output variability: A theory for the accuracy of rapid motor acts. *Psychological review*, *86*(5), 415–451.

Schneider, N., Wilkes, J., Grandt, M., & Schlick, C. M. (2008). Investigation of input devices for the age-differentiated design of human-computer interaction. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *52*(2), 144–148.

Sears, A., & Shneiderman, B. (1991). High precision touchscreens: Design strategies and comparisons with a mouse. *International Journal of Man-Machine Studies*, *34*(4), 593–613.

Smith, M. W., Sharit, J., & Czaja, S. J. (1999). Aging, motor control, and the performance of computer mouse tasks. *Human factors*, *41*(3), 389–396.

Soukoreff, R. W., & MacKenzie, I. S. (2004). Towards a standard for pointing device evaluation, perspectives on 27 years of fitts' law research in hci. *International Journal of Human-Computer Studies*, *61*(6), 751–789.

Strauss, E., Sherman, E. M., Spreen, O., et al. (2006). *A compendium of neuropsychological tests: Administration, norms, and commentary*. American Chemical Society.

Sultana, A. (2015). Performance evaluation for touch-based interaction of older adults. *ACM SIGACCESS Accessibility and Computing*, (111), 38–41.

Sultana, A., & Moffatt, K. (2013). Automatic error detection from pointing device input data. *Proceedings of the Association for Information Science and Technology*, *50*(1), 1–3.

Sultana, A., & Moffatt, K. (2017). Target selection difficulties of older adults with small touchscreen devices. *Proceedings of the Workshop on Designing Mobile Interactions for the Aging Populations, The 35th ACM SIGCHI Conference on Human Factors in Computing Systems (CHI) 2017*, 25–28.

Sultana, A., & Moffatt, K. (2018). 3-D finger trajectory tracking, modelling and visualizing tool for accessible touchscreen interface for older adults [Demo presented at the AGE-WELL Annual Conference 2018, October 16 – 17, Vancouver, BC, Canada]. https://agewell-nce.ca/wp-content/uploads/2018/12/2018-Abstract-Booklet.pdf

Sultana, A., & Moffatt, K. (2019). Effects of aging on small target selection with touch input. *ACM Transactions on Accessible Computing (TACCESS)*, *12*(1), 1. https://doi.org/10.1145/3300178

Sultana, A., Xu, J., & Moffatt, K. (2018). Towards accessible touchscreen interfaces for older adults: Modeling and visualizing finger trajectories. *Proceedings of the Workshop on Designing Interactions for the Aging Populations, The 36th ACM SIGCHI Conference on Human Factors in Computing Systems (CHI) 2018*, 22–27.

Tabachnick, B. G., & Fidell, L. S. (2001). Using multivariate statistics. allyn and bacon. *Needham Heights, MA*.

Taveira, A. D., & Choi, S. D. (2009). Review study of computer input devices and older users. *Intl. Journal of Human–Computer Interaction*, *25*(5), 455–474.

Topo, P. (2009). Technology studies to meet the needs of people with dementia and their caregivers a literature review. *Journal of Applied Gerontology*, *28*(1), 5–37.

Trewin, S. (2003). Automating accessibility: The dynamic keyboard. *Proceedings of the 6th International ACM SIGACCESS Conference on Computers and Accessibility*, 71–78. https://doi.org/10.1145/1028630.1028644

Trewin, S., Keates, S., & Moffatt, K. (2006). Developing steady clicks:: A method of cursor assistance for people with motor impairments. *Proceedings of the 8th international ACM SIGACCESS conference on Computers and accessibility*, 26–33.

Vogel, D., & Baudisch, P. (2007). Shift: A technique for operating pen-based interfaces using touch. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 657–666. https://doi.org/10.1145/1240624.1240727

Vuletic, T., Duffy, A., Hay, L., McTeague, C., Campbell, G., & Grealy, M. (2019). Systematic literature review of hand gestures used in human computer interaction interfaces. *International Journal of Human-Computer Studies*, *129*, 74–94.

Walker, N., Philbin, D. A., & Fisk, A. D. (1997). Age-related differences in movement control: Adjusting submovement structure to optimize performance. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *52*(1), P40–P53.

Welford, A. (1968). *Fundamentals of skill*. Methuen. https://psycnet.apa.org/record/1968-35018-000

Welford, A. (1981). Signal, noise, performance, and age. *Human Factors*, *23*(1), 97–109.

Welford, A. (1988). Reaction time, speed of performance, and age. *Annals of the New York Academy of Sciences*, *515*(1), 1–17.

Welford, A., Norris, A., & Shock, N. (1969). Speed and accuracy of movement and their changes with age. *Acta psychologica*, *30*, 3–15.

Wobbrock, J. O. (2019). Improving pointing in graphical user interfaces for people with motor impairments through ability-based design. In I. R. Management Association (Ed.), *Human performance technology: Concepts, methodologies, tools, and applications* (pp. 1193–1243). IGI Global. https://doi.org/10.4018/978-1-5225-8356-1.ch059

Wobbrock, J. O., Fogarty, J., Liu, S.-Y., Kimuro, S., & Harada, S. (2009). The angle mouse: Target-agnostic dynamic gain adjustment based on angular deviation. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1401–1410. https://doi.org/10.1145/1518701.1518912

Wobbrock, J. O., & Gajos, K. Z. (2008). Goal crossing with mice and trackballs for people with motor impairments: Performance, submovements, and design directions. *ACM Transactions on Accessible Computing (TACCESS)*, *1*(1), 4.

Wobbrock, J. O., Kane, S. K., Gajos, K. Z., Harada, S., & Froehlich, J. (2011). Ability-based design: Concept, principles and examples. *ACM Transactions on Accessible Computing (TACCESS)*, *3*(3), 9.

Worden, A., Walker, N., Bharat, K., & Hudson, S. (1997). Making computers easier for older adults to use: Area cursors and sticky icons. *CHI*, *97*, 266–271.

Wu, J., Reyes, G., White, S. C., Zhang, X., & Bigham, J. P. (2020). Towards recommending accessibility features on mobile devices. *The 22nd International ACM SIGACCESS Conference on Computers and Accessibility*. https://doi.org/10.1145/3373625.3418007

Xi, Y., Cho, S., Jeong, Y.-S., Cho, K., & Um, K. (2014). Surface touch interaction method using inverted leap motion device. In J. J. Park, P. Yi, C.-S. Kim, & Y. Yang (Eds.), *Future information technology* (pp. 469–474). Springer.

Yan, J. H. (2000). Effects of aging on linear and curvilinear aiming arm movements. *Experimental aging research*, *26*(4), 393–407.

Zhai, S., Buxton, W., & Milgram, P. (1994). The "silk cursor" investigating transparency for 3d target acquisition. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 459–464.

Appendix A

Data Collection Forms

This appendix includes the participant background data collection form and the post-experiment questionnaire that were used in the error analysis study and the trajectory analysis study presented in Chapters 3 - 5. We used the data collection forms for Digit Symbol Substitution Test (DSST), North American Adult Reading Test (NAART), and Letter Set Test (LST) from Strauss et al. (2006).

Computer Usability Study: Background Questionnaire

Instructions: Please answer the following questions to the best of your ability. If you have any questions, please do not hesitate to ask the researcher for help or clarification.

Part I: Personal Information

1. What is your gender? ❑ Male ❑ Female

2. What is your age? __________

3. Please indicate the highest level of education you have obtained. (Where space is provided, please specify the degree or program.)

   ❑ Some school

   ❑ Some high school

   ❑ Completed high school

   ❑ Some post-secondary education: ____________________________________

   ❑ Completed community college: _____________________________________

   ❑ Completed undergraduate degree: ___________________________________

   ❑ Some graduate or professional school: _______________________________

   ❑ Completed post-graduate degree: ____________________________________

   ❑ Other, please specify: ____

4. What is your primary job or profession (what do you do for a living)? Please select the most appropriate alternative.

   ❑ Full time: ____

   ❑ Part time: ____

   ❑ Retired (previous job): ________________________________

Part II: Computer/Touchscreen Device Experience

Please note that for the purposes of this questionnaire, the term computer refers to any of the following: desktop, laptop, notebook, etc., and the term handheld touch-screen device refers to any of the following: iPad, iPhone, tablet, smartphone, PDA, PalmPilot, etc

1. When did you first use a computer (e.g., desktop, laptop/notebook, etc.)?

   ❏ pre-1960 ❏ 1970–1979 ❏ 1990–1999 ❏ 2010–present

   ❏ 1960–1969 ❏ 1980–1989 ❏ 2000–2009 ❏ Never

2. What kinds of computers have you used? *Tick all that apply.*

   ❏ PC (Windows) ❏ Laptop / Notebook

   ❏ PC (Linux) ❏ Tablet PC

   ❏ Mac / Apple ❏ Hand-held (PDA/PalmPilot, etc.)

   ❏ Unix ❏ Not sure ❏ Other: __________________

3. When did you first use a hand-held touchscreen device (e.g., iPad, iPhone, tablet, smartphone, PDA, etc.)?

   ❏ pre-1980 ❏ 1990–1999 ❏ 2010–present

   ❏ 1980–1989 ❏ 2000–2009 ❏ Never

4. What kinds of hand-held touchscreen devices have you used? *Tick all that apply.*

   ❏ iPad ❏ Android Tablet

   ❏ iPhone ❏ Android Phone

   ❏ Kindle ❏ Not sure

   ❏ PDA/PalmPilot, etc ❏ Other: __________________

5. Do you use a computer or a hand-held touchscreen device for work?

   Computers: ❏ Yes _______ hours per day or _______ hours per week

   ❏ No ❏ N/A

   Touchscreen Devices: ❏ Yes ______ hours per day or ______ hours per week

   ❏ No ❏ N/A

6. Do you use a computer or hand-held touchscreen device for leisure or personal tasks?

   Computers: ❏ Yes _______ hours per day or _______ hours per week

   ❏ No ❏ N/A

   Touchscreen Devices: ❏ Yes ______ hours per day or ______ hours per week

   ❏ No ❏ N/A

7. How familiar are you with the following types of applications?

	Entirely Unfamiliar	Mostly Unfamiliar	Mostly Familiar	Very Familiar
Web Browser (e.g., Chrome, Safari, IE)	❏	❏	❏	❏
Social Media (e.g, Facebook, Twitter)	❏	❏	❏	❏
Email (e.g., Outlook, Gmail , Hotmail)	❏	❏	❏	❏
Messenger (e.g., Skype, FaceTime, WhatsApp, Viber)	❏	❏	❏	❏
Word Processor (e.g., MS Word)	❏	❏	❏	❏
Spreadsheet (e.g., Excel, Lotus 1-2-3)	❏	❏	❏	❏
Graphics (e.g., Photoshop, Corel Draw)	❏	❏	❏	❏
Presentation Software (e.g., Powerpoint)	❏	❏	❏	❏
Database (e.g., MySql, MS Access)	❏	❏	❏	❏
Music/Video (e.g., iTunes, Quicktime)	❏	❏	❏	❏
Computer games	❏	❏	❏	❏
Other ______________________	❏	❏	❏	❏

8. Which of the following have you done with a hand-held device? *Tick all that apply.*

❏ I have made phone calls or made a call with Skype or a similar software.

❏ I have composed, and send a text message or an email.

❏ I have used social media (e.g., Facebook, Twitter, Pinterest).

❏ I have searched for information on internet.

❏ I have made a purchase online.

❏ I have transferred data (e.g., photo, file) from a hand-held device to a computer.

❏ I have customized options or preferences within an application.

❏ I have installed or updated an application.

❏ I have installed or updated an operating system.

❏ I have reset a hand-held device to the original factory settings.

❏ I have added memory.

9. How would use characterize yourself in terms of your knowledge of computers and hand-held touchscreen devices?

Computers:	❏ Basic	❏ Moderate	❏ Extensive
Touchscreen Devices:	❏ Basic	❏ Moderate	❏ Extensive

10. Have you ever attended a course?

    Computers: ❏ Yes, please specify: ____________________ ❏ No

    Touchscreen Devices: ❏ Yes, please specify: ____________________ ❏ No

11. Is there any other relevant information about your use of computers that you would like to note here?

    ____

    ____

    ____

    ____

    ____

    ____

Researcher's Initials: ________________

Date: ______________________________

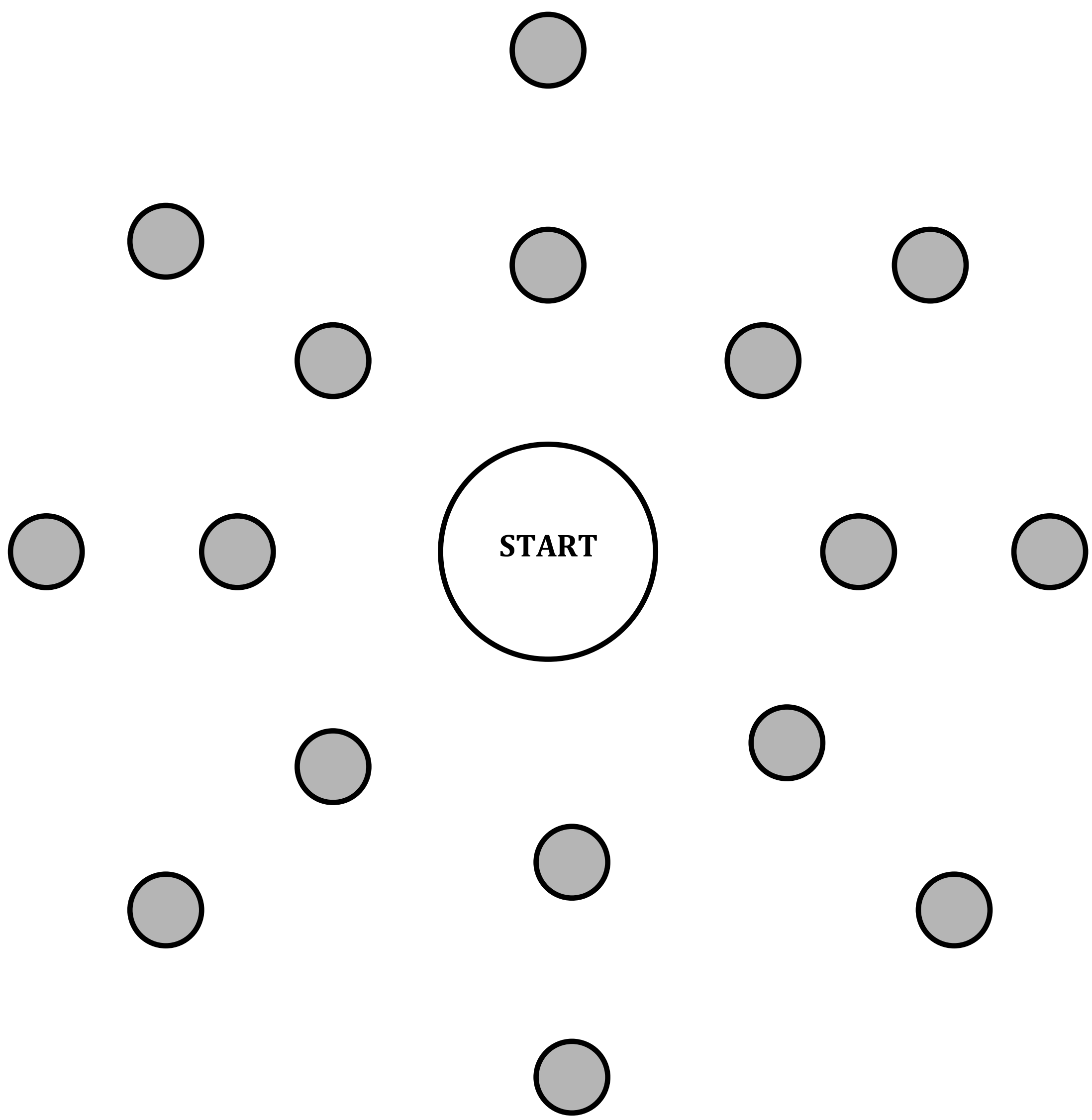
Participant ID # _______________

Computer Usability Study: Post-Experiment Questionnaire

Please answer the following questions to the best of your ability.

In the two-dimensional Fitts' task you have selected targets of three different sizes: small, medium and large. The targets were also located in either smaller or larger distance. Please rate your experience for different target size, different target distance, and different target angle on the following criteria: Speed, Error, Difficulty Level, and Preference.

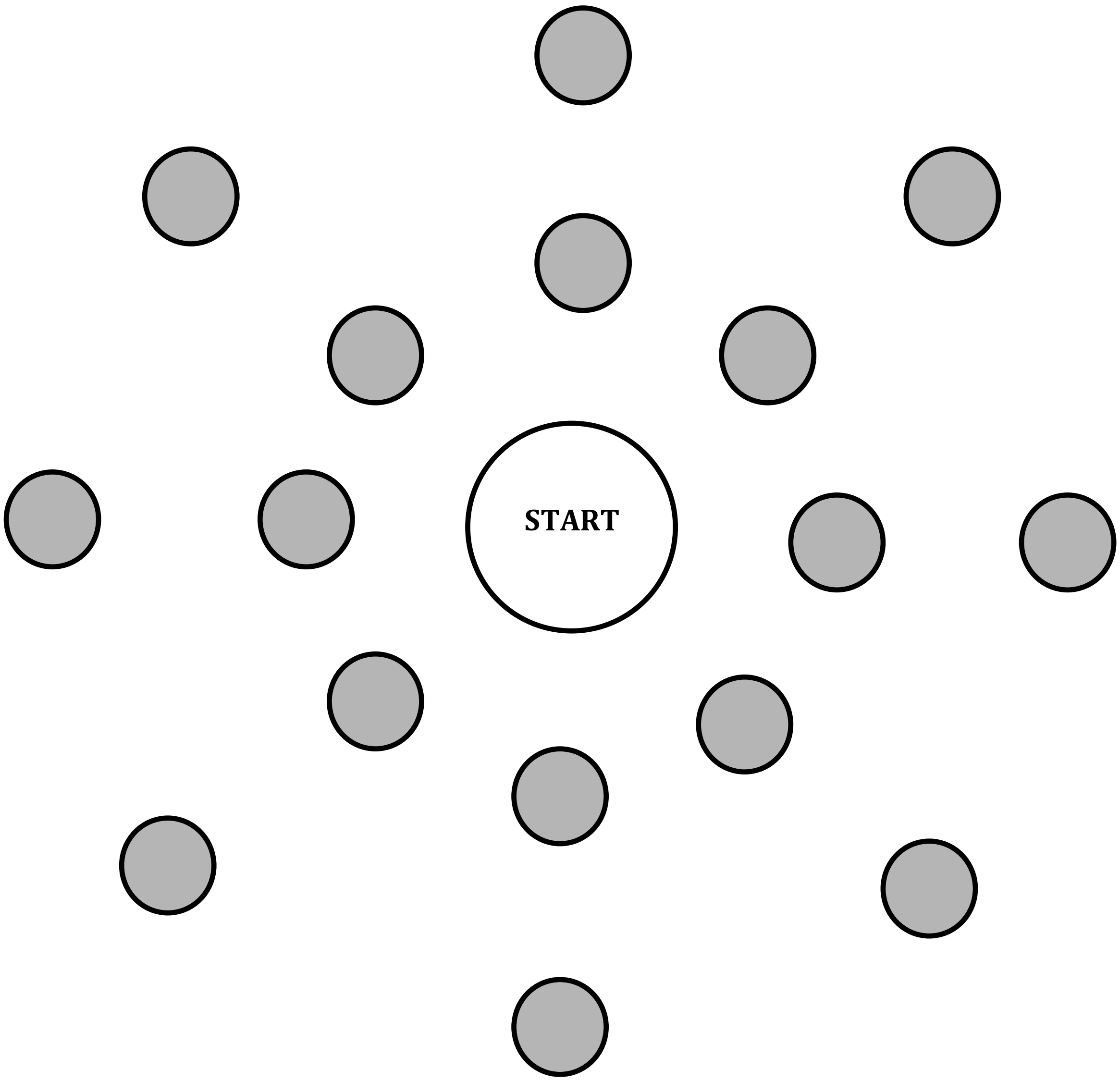
Small Size Target



Speed Error Difficulty Level Preference

Participant ID # _______________

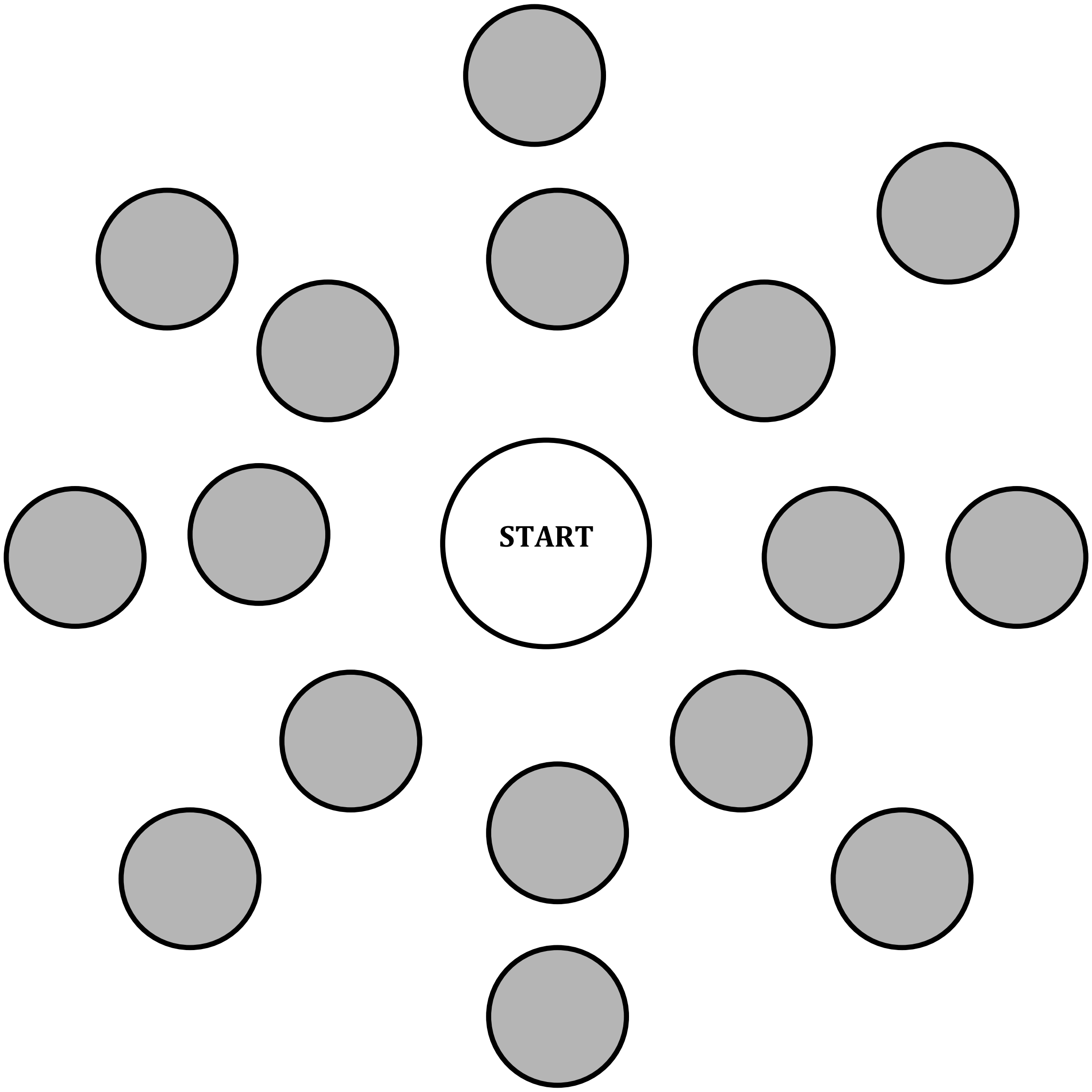
Medium Size Target



Speed Error Difficulty Level Preference

Participant ID # _______________

Large Size Target



Speed Error Difficulty Level Preference

Participant ID # ________________

Is there any other relevant information about the study that you would like to note here?

____

____

____

____

____

____

____

____

____

____

____

Researcher's Initial ____________________

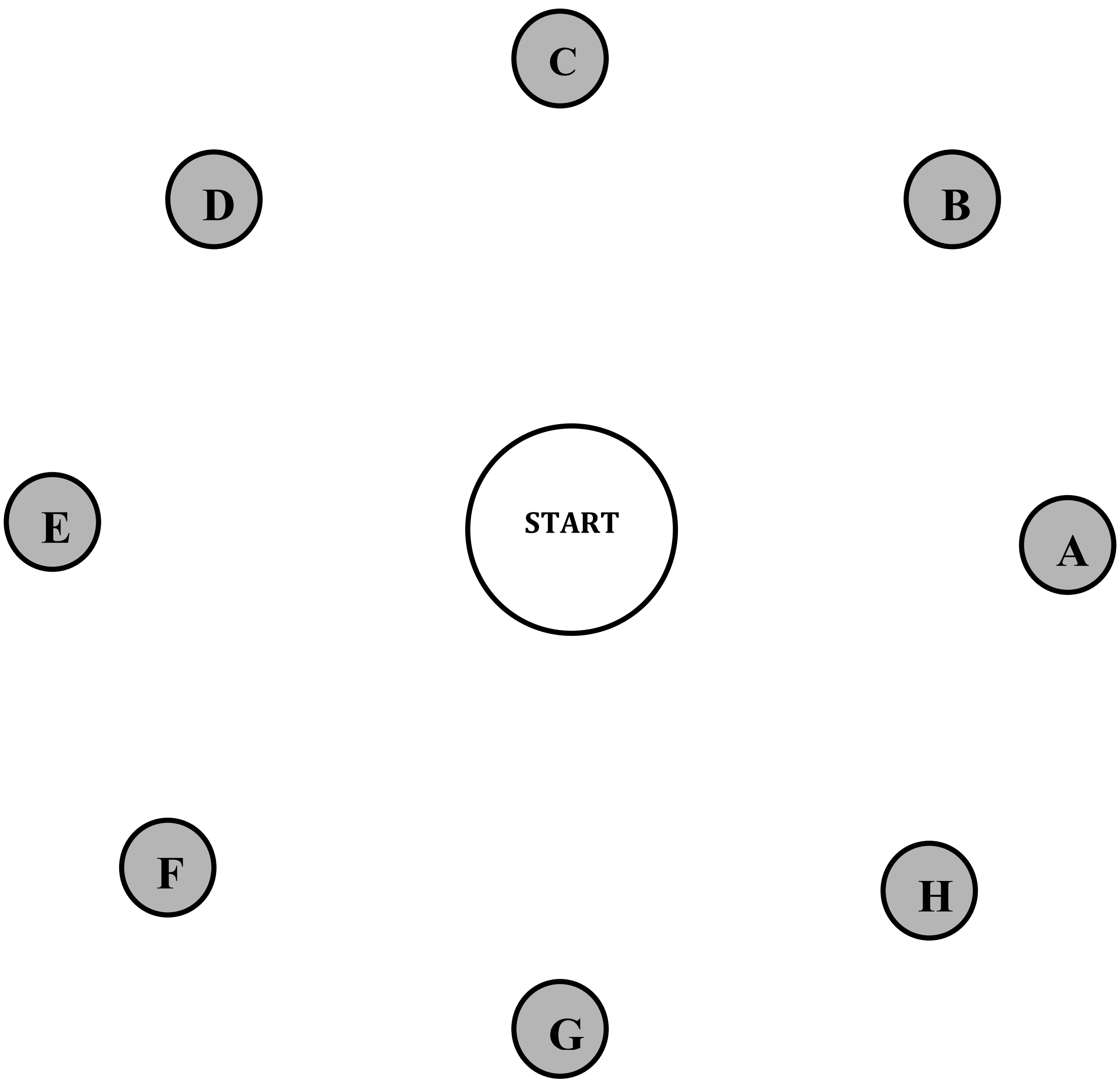
Date: ______________________________

Participant ID # _______________

Computer Usability Study: Post-Experiment Questionnaire

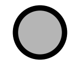
Please answer the following questions to the best of your ability.

In the target selection task you have selected targets of four different sizes: small, medium, large and extra large. The targets were also located in smaller, medium or larger distance. Please rate your experience for different target size, different target distance, and different target angle on the following criteria: **Speed, Error, Difficulty Level, and Preference**.



Participant ID # ____________

Small Targets (4.88 mm)



Speed (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	**Small Distance (20 mm)**	**Medium Distance (30 mm)**	**Large Distance (40 mm)**
A			
B			
C			
D			
E			
F			
G			
H			

Error (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	**Small Distance (20 mm)**	**Medium Distance (30 mm)**	**Large Distance (40 mm)**
A			
B			
C			
D			
E			
F			
G			
H			

Difficulty Level (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

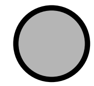
Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Preference (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # ________________

Medium Targets (7.22 mm)



Speed (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Error (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # ______________

Difficulty Level (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

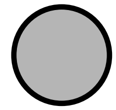
Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Preference (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # ________________

Large Targets (9.22 mm)



Speed (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Error (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # ________________

Difficulty Level (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

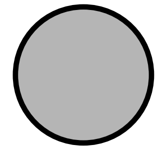
Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Preference (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # ________________

Extra Large Targets (12.22 mm)



Speed (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Error (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # ________________

Difficulty Level (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Preference (Scale: 1 – 5, 1 = Lowest, 5 = Highest)

Angle	Small Distance (20 mm)	Medium Distance (30 mm)	Large Distance (40 mm)
A			
B			
C			
D			
E			
F			
G			
H			

Participant ID # _______________

Is there any other relevant information about the study that you would like to note here?

____

____

____

____

____

____

____

____

____

____

____

Researcher's Initial ____________________

Date: _______________________________

Appendix B

Additional Results from Error Analysis Study

This appendix includes all additional results from the error analysis study that was presented in Chapter 3. Section B.1 presents results of the inferential statistical analysis from the error analysis study. Section B.2 presents the histograms of miss and slip error distribution across target widths.

B.1 Inferential Statistics from Selection Error Analysis Study

We present all inferential statistics from the error analysis study in this section (see Tables B.1 - B.5). All main and interaction effects reported here are from repeated measure ANOVAs having target width, amplitude and angle as within subject and age as between subject factors. All pairwise comparisons were corrected with a Bonferroni correction. Mauchly's test was conducted to identify sphericity violations and corrected with Greenhouse-Geisser corrections; where degrees of freedom (*df*) are non-integer, a correction has been applied.

Table B.1 Statistical Inference from Movement Time (MT)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,33} = 19.01$	$p < .0005$	$\eta_p^2 = .37$
Width	$F_{1.17,38.59} = 37.46$	$p < .00001$	$\eta_p^2 = .53$
Amplitude	$F_{1,33} = 119.40$	$p < .00001$	$\eta_p^2 = .78$
Angle	$F_{4.73,156.07} = 17.13$	$p < .00001$	$\eta_p^2 = .34$
Age × Width	$F_{1.17,38.59} = 0.19$	$p = .701$	$\eta_p^2 = .41$
Age × Amplitude	$F_{1,33} = 0.01$	$p = .930$	$\eta_p^2 = .00$
Age × Angle	$F_{4.73,156.07} = 1.47$	$p = .206$	$\eta_p^2 = .04$
Age × Width × Amplitude	$F_{2,66} = 0.44$	$p = .648$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{7.90,260.71} = 0.50$	$p = .851$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{4.99,164.94} = 0.26$	$p = .934$	$\eta_p^2 = .01$
Age × Width × Amplitude × Angle	$F_{8.13,268.29} = 1.31$	$p = .237$	$\eta_p^2 = .04$
Width × Amplitude	$F_{2,66} = 3.14$	$p < .05$	$\eta_p^2 = .09$
Width × Angle	$F_{7.90,260.71} = 1.07$	$p = .386$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{4.99,164.94} = 2.03$	$p = .077$	$\eta_p^2 = .06$
Width × Amplitude × Angle	$F_{8.13,268.29} = 0.90$	$p = .518$	$\eta_p^2 = .03$

B.2 Miss and Slip Error Distribution

In this section we present the histograms of error distributions of miss and slip errors across age groups and target widths (Figures B.1 - B.16). All of the histograms have intervals of 1/4th width of the corresponding target widths. For the histograms showing all errors have intervals of 1/4th width of the smallest (4.88 mm) targets. In the width specific histograms we mapped the error distribution categories from prior work for mouse (Keates & Trewin,

Table B.2 Statistical Inference from Error Rate

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,33} = 42.23$	$p < .0001$	$\eta_p^2 = .56$
Width	$F_{1.35,44.68} = 153.60$	$p < .0001$	$\eta_p^2 = .82$
Amplitude	$F_{1,33} = 0.73$	$p = .398$	$\eta_p^2 = .02$
Angle	$F_{4.66,153.73} = 1.04$	$p = .397$	$\eta_p^2 = .03$
Age × Width	$F_{1.35,44.68} = 27.68$	$p < .0001$	$\eta_p^2 = .46$
Age × Amplitude	$F_{1,33} = 4.01$	$p = .054$	$\eta_p^2 = .11$
Age × Angle	$F_{4.66,153.73} = 0.52$	$p = .751$	$\eta_p^2 = .02$
Age × Width × Amplitude	$F_{2,66} = 0.08$	$p = .927$	$\eta_p^2 = .00$
Age × Width × Angle	$F_{8.13,268.18} = 0.55$	$p = .821$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{7,231} = 0.65$	$p = .711$	$\eta_p^2 = .02$
Age × Width × Amplitude × Angle	$F_{8.40,277.27} = 1.08$	$p = .375$	$\eta_p^2 = .03$
Width × Amplitude	$F_{2,66} = 0.10$	$p = .901$	$\eta_p^2 = .00$
Width × Angle	$F_{8.13,268.18} = 0.93$	$p = .496$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{7,231} = 1.83$	$p = .082$	$\eta_p^2 = .05$
Width × Amplitude × Angle	$F_{8.40,277.27} = 0.97$	$p = .464$	$\eta_p^2 = .03$

Table B.3 Statistical Inference from Miss Errors

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,33} = 36.27$	$p < .0001$	$\eta_p^2 = .52$
Width	$F_{1.27,41.96} = 141.36$	$p < .0001$	$\eta_p^2 = .81$
Amplitude	$F_{1,33} = 0.09$	$p = .768$	$\eta_p^2 = .00$
Angle	$F_{4.56,150.55} = 1.22$	$p = .302$	$\eta_p^2 = .04$
Age × Width	$F_{1.27,41.96} = 27.71$	$p < .00001$	$\eta_p^2 = .46$
Age × Amplitude	$F_{1,33} = 2.66$	$p = .112$	$\eta_p^2 = .08$
Age × Angle	$F_{4.56,150.55} = 0.88$	$p = .492$	$\eta_p^2 = .03$
Age × Width × Amplitude	$F_{1.71,56.26} = 0.26$	$p = .735$	$\eta_p^2 = .02$
Age × Width × Angle	$F_{7.47,246.36} = 0.38$	$p = .923$	$\eta_p^2 = .01$
Age × Amplitude × Angle	$F_{7,231} = 0.90$	$p = .511$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{8.20,270.47} = 0.52$	$p = .848$	$\eta_p^2 = .02$
Width × Amplitude	$F_{1.71,56.26} = 0.80$	$p = .438$	$\eta_p^2 = .02$
Width × Angle	$F_{7.47,246.36} = 0.79$	$p = .600$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{7,231} = 1.96$	$p = .062$	$\eta_p^2 = .06$
Width × Amplitude × Angle	$F_{8.20,270.47} = 0.68$	$p = .714$	$\eta_p^2 = .02$

Table B.4 Statistical Inference from Slip Errors

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,33} = 9.94$	$p < .005$	$\eta_p^2 = .23$
Width	$F_{1.34,44.28} = 7.27$	$p = .0054$	$\eta_p^2 = .18$
Amplitude	$F_{1,33} = 1.42$	$p = .243$	$\eta_p^2 = .04$
Angle	$F_{3.81,125.60} = 0.43$	$p = .776$	$\eta_p^2 = .01$
Age × Width	$F_{1.34,44.28} = 1.74$	$p = .195$	$\eta_p^2 = .04$
Age × Amplitude	$F_{1,33} = 4.01$	$p = .054$	$\eta_p^2 = .11$
Age × Angle	$F_{3.81,125.60} = 0.44$	$p = .771$	$\eta_p^2 = .01$
Age × Width × Amplitude	$F_{1.64,54.18} = 0.31$	$p = .694$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{6.77,233.40} = 0.87$	$p = .526$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{4.43,146.26} = 0.42$	$p = .814$	$\eta_p^2 = .01$
Age × Width × Amplitude × Angle	$F_{5.35,176.62} = 1.24$	$p = .291$	$\eta_p^2 = .04$
Width × Amplitude	$F_{1.64,54.18} = 1.32$	$p = .273$	$\eta_p^2 = .04$
Width × Angle	$F_{6.77,233.40} = 0.66$	$p = .700$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{4.43,146.26} = 0.64$	$p = .651$	$\eta_p^2 = .02$
Width × Amplitude × Angle	$F_{5.35,176.62} = 0.57$	$p = .735$	$\eta_p^2 = .02$

Table B.5 Statistical Inference from Finger Pressure

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,33} = 8.18$	$p < .01$	$\eta_p^2 = .20$
Width	$F_{2,66} = 28.77$	$p < .00001$	$\eta_p^2 = .47$
Amplitude	$F_{1,33} = 1.06$	$p = .310$	$\eta_p^2 = .03$
Angle	$F_{3.42,231} = 10.67$	$p < .00001$	$\eta_p^2 = .24$
Age × Width	$F_{2,66} = 0.76$	$p = .474$	$\eta_p^2 = .02$
Age × Amplitude	$F_{1,33} = 0.65$	$p = .424$	$\eta_p^2 = .02$
Age × Angle	$F_{3.43,113.26} = 2.07$	$p = .1$	$\eta_p^2 = .06$
Age × Width × Amplitude	$F_{2,66} = 0.35$	$p = .706$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{8.02,264.51} = 0.80$	$p = .602$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{4.58,151.06} = 0.90$	$p = .509$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{7.96,262.82} = 0.71$	$p = .681$	$\eta_p^2 = .02$
Width × Amplitude	$F_{2,66} = 1.20$	$p = .307$	$\eta_p^2 = .04$
Width × Angle	$F_{8.02,264.51} = 0.79$	$p = .617$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{4.58,151.06} = 2.48$	$p < .05$	$\eta_p^2 = .07$
Width × Amplitude × Angle	$F_{7.96,262.82} = 1.54$	$p = .143$	$\eta_p^2 = .05$

2005) and pen (Moffatt & McGrenere, 2007) interaction. All histograms conform with the error distributions from prior work for, i.e., having more errors closer to the target boundaries.

B.2.1 Miss Error Distribution

Histograms for miss error distributions are shown in Figures B.1 - B.8.

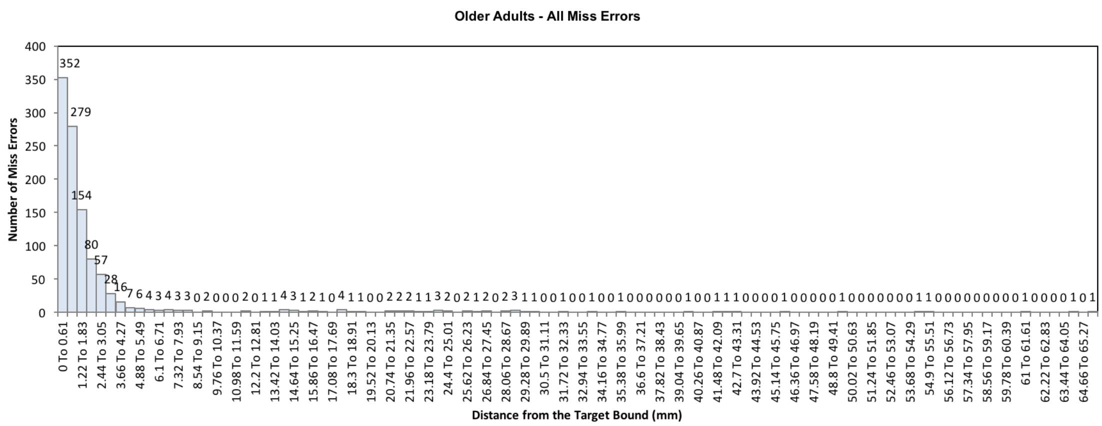


Figure B.1 Histogram of all miss errors for older adults.

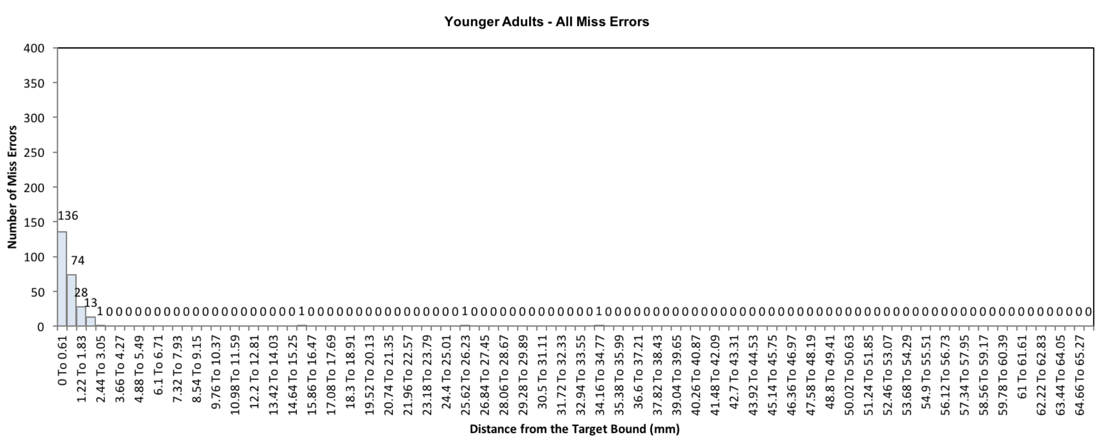


Figure B.2 Histogram of all miss errors for younger adults.

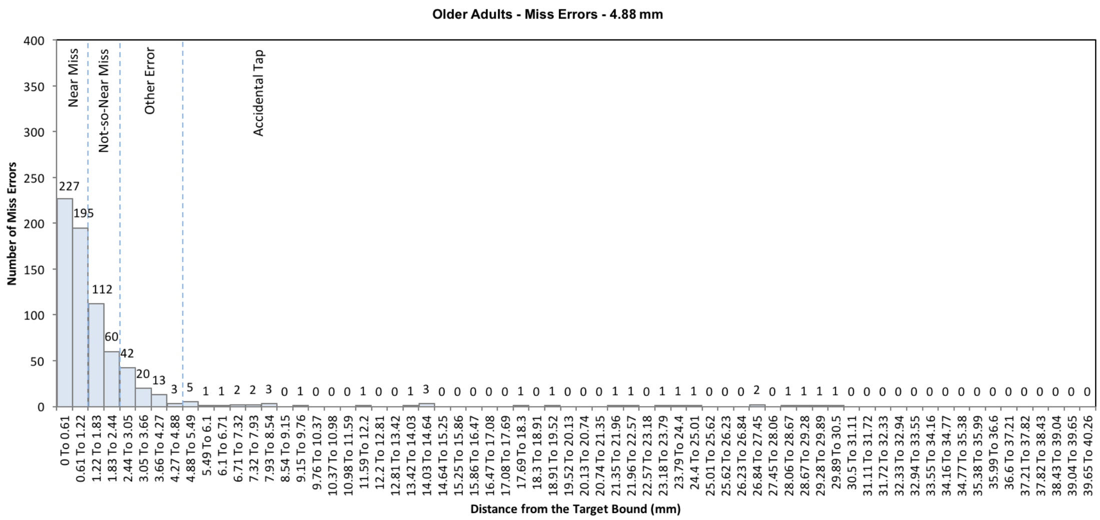


Figure B.3 Histogram of all miss errors for older adults with the smallest (4.88 mm) targets. For space constraints, we did not show the last five miss errors in the histogram, one error each in the 42.70-43.31, 54.29-54.90, 64.05-64.66 and 65.27-65.88 mm intervals.

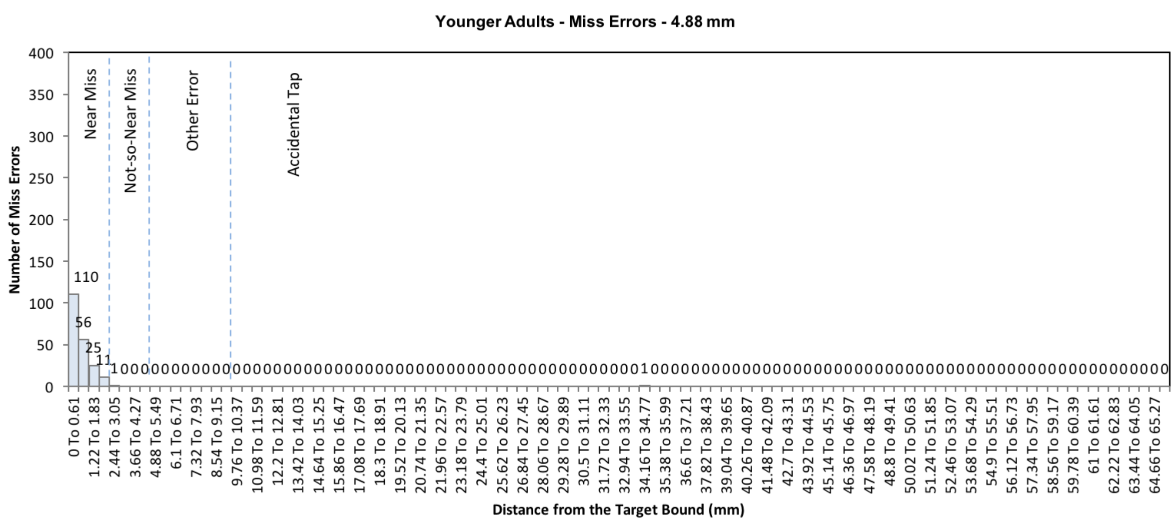


Figure B.4 Histogram of all miss errors for younger adults with the smallest (4.88 mm) targets.

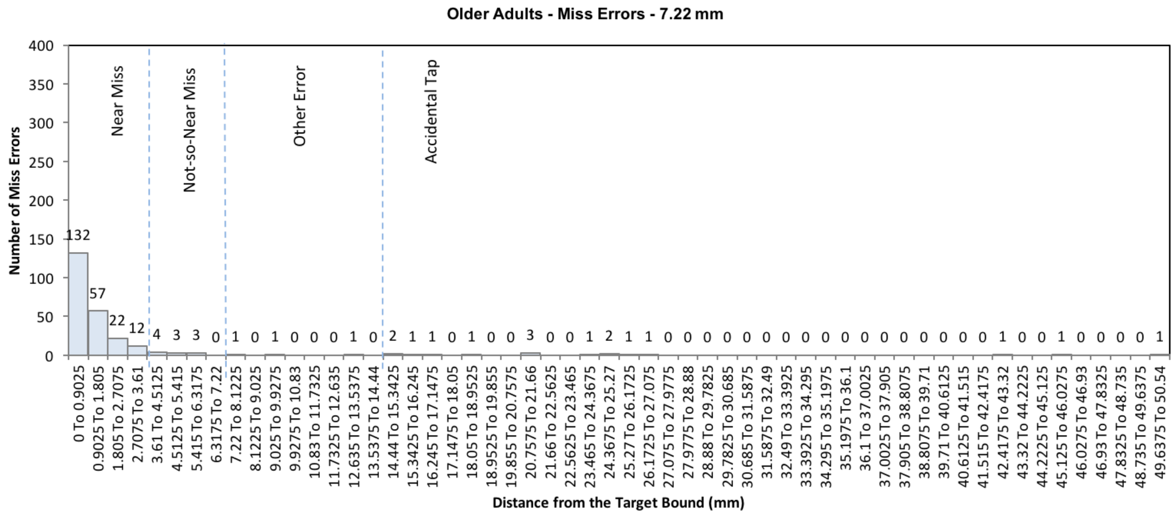


Figure B.5 Histogram of all miss errors for older adults with the medium (7.22mm) targets. For space constraints, we did not show the last three miss errors in the histogram, one error each in the 42.42–43.32mm, 45.13– 46.03mm, and 49.64–50.54mm intervals.

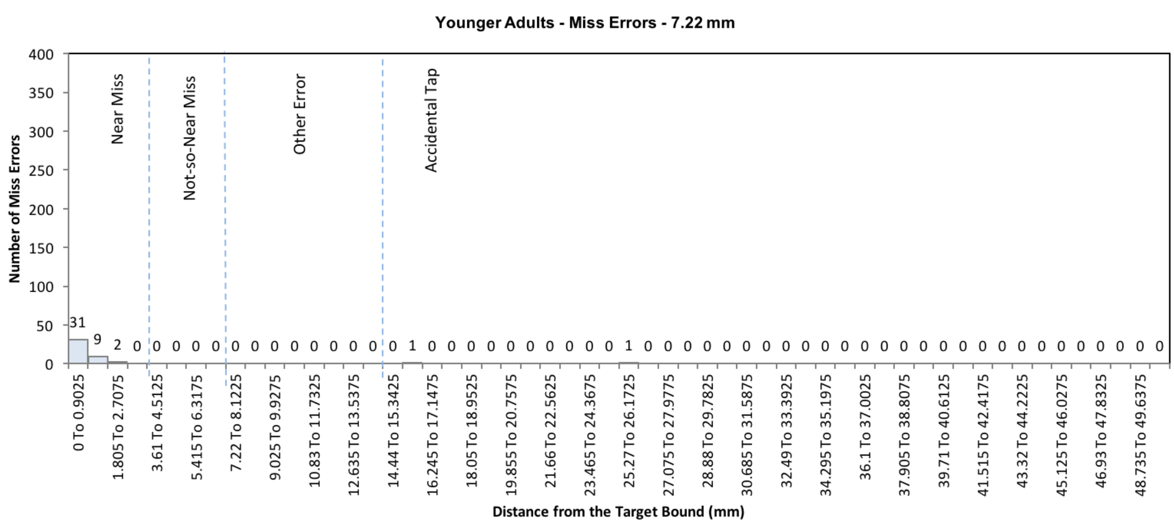


Figure B.6 Histogram of all miss errors for younger adults with the medium (7.22mm) targets.

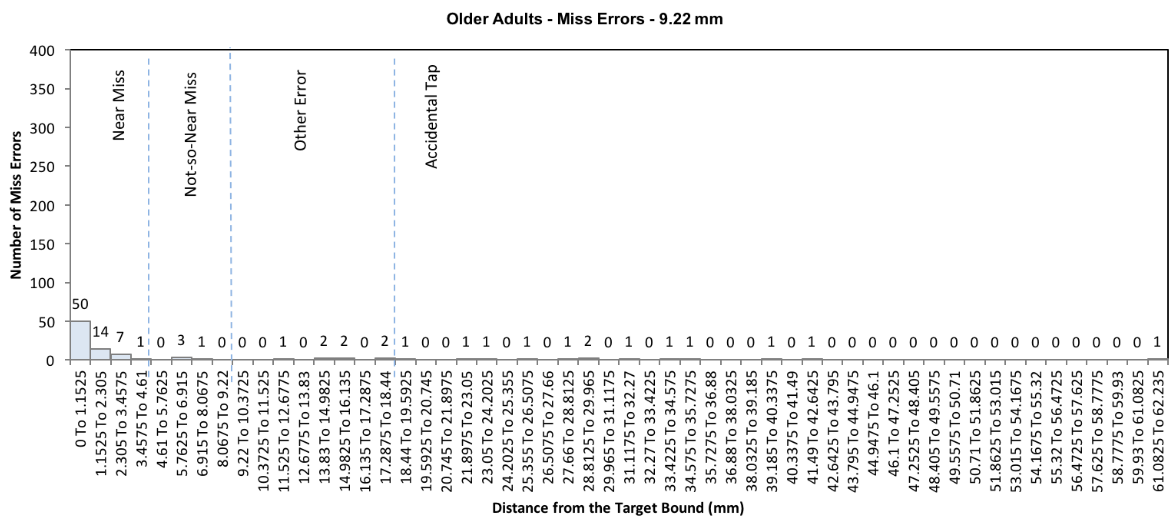


Figure B.7 Histogram of all miss errors for older adults with the largest (9.22mm) targets.

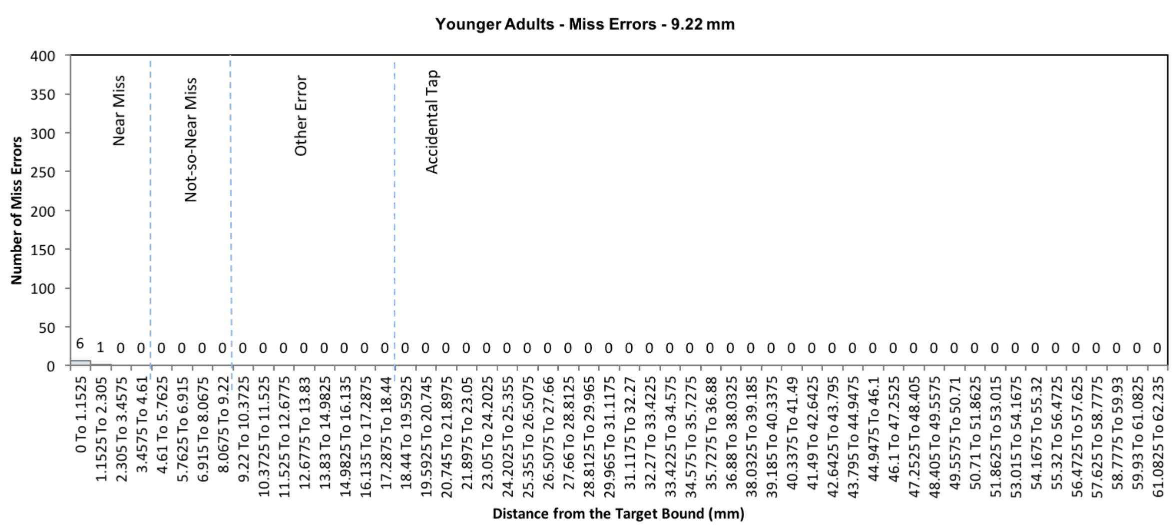


Figure B.8 Histogram of all miss errors for younger adults with the largest (9.22mm) targets.

B.2.2 Slip Error Distribution

Histograms for miss error distributions are shown in Figures B.9 - B.16.

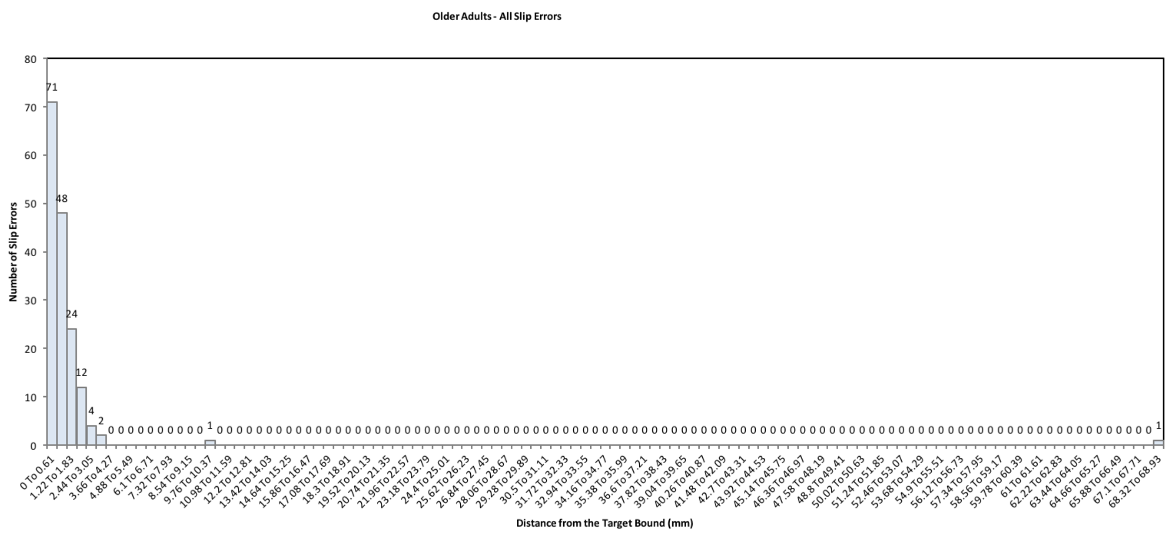


Figure B.9 Histogram of all slip errors for older adults.

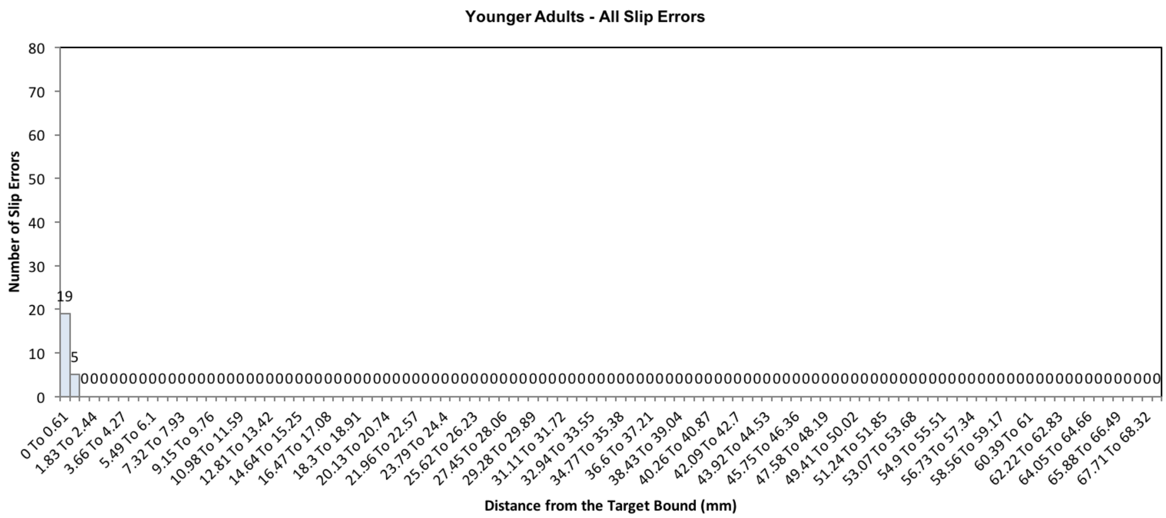


Figure B.10 Histogram of all slip errors for younger adults.

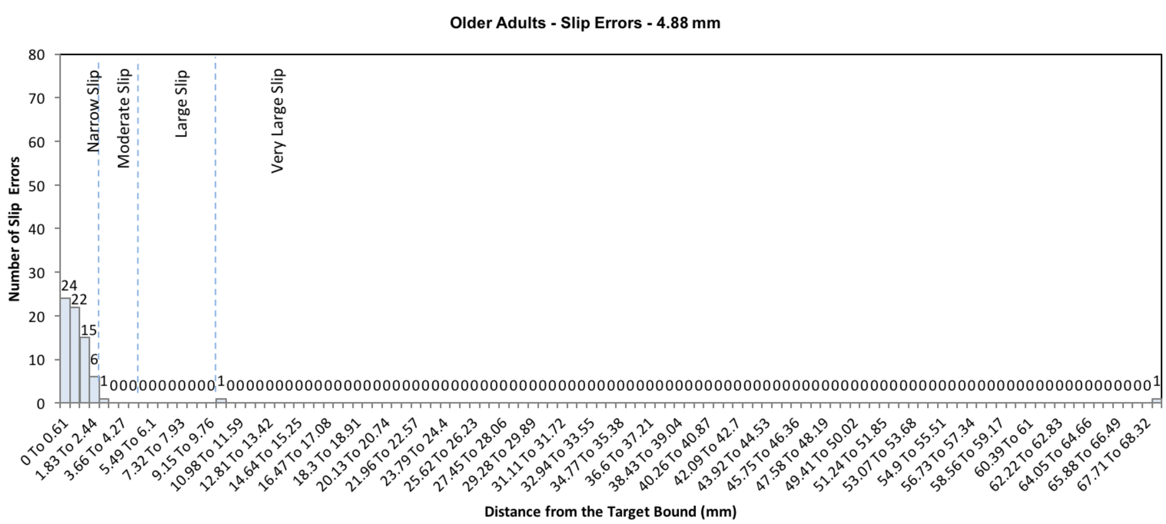


Figure B.11 Histogram of all slip errors for older adults with the smallest (4.88mm) targets. For space constraints, we did not show the last slip errors in the histogram in the 68.32–68.92mm interval.

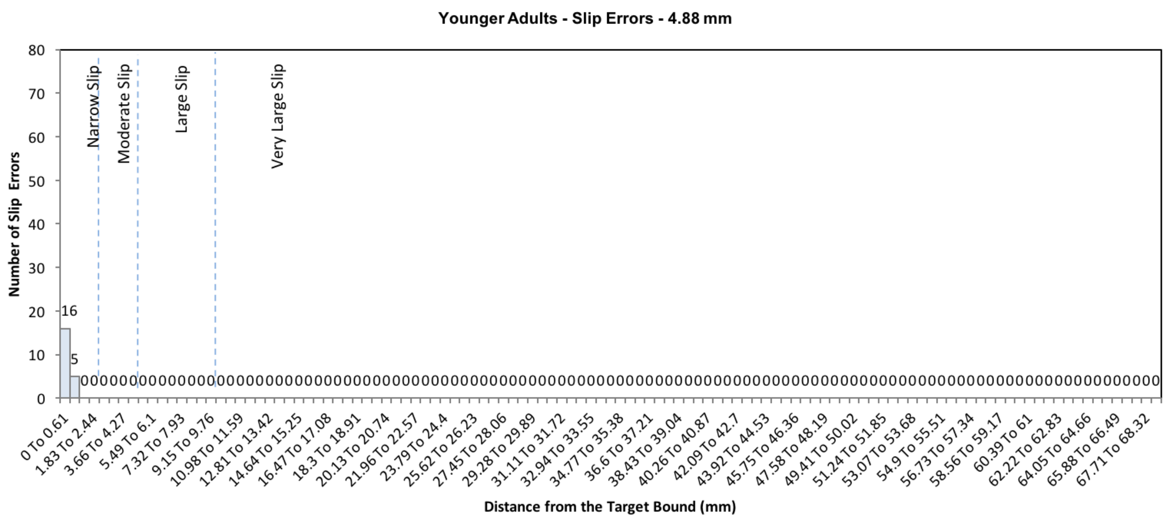


Figure B.12 Histogram of all slip errors for younger adults with the smallest (4.88mm) targets.

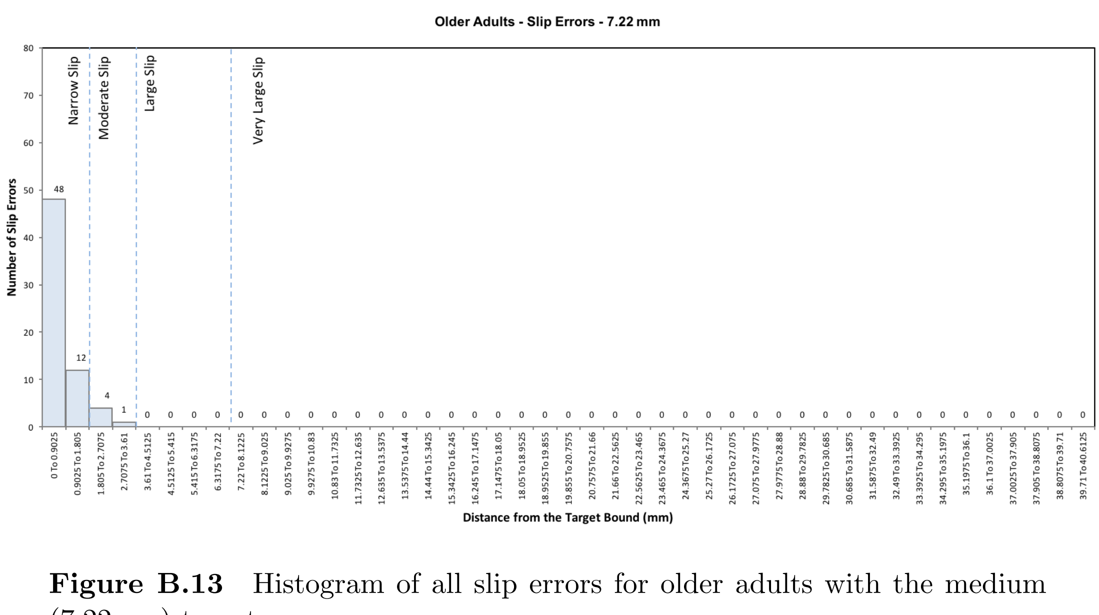


Figure B.13 Histogram of all slip errors for older adults with the medium (7.22mm) targets.

Figure B.14 Histogram of all slip errors for younger adults with the medium (7.22mm) targets.

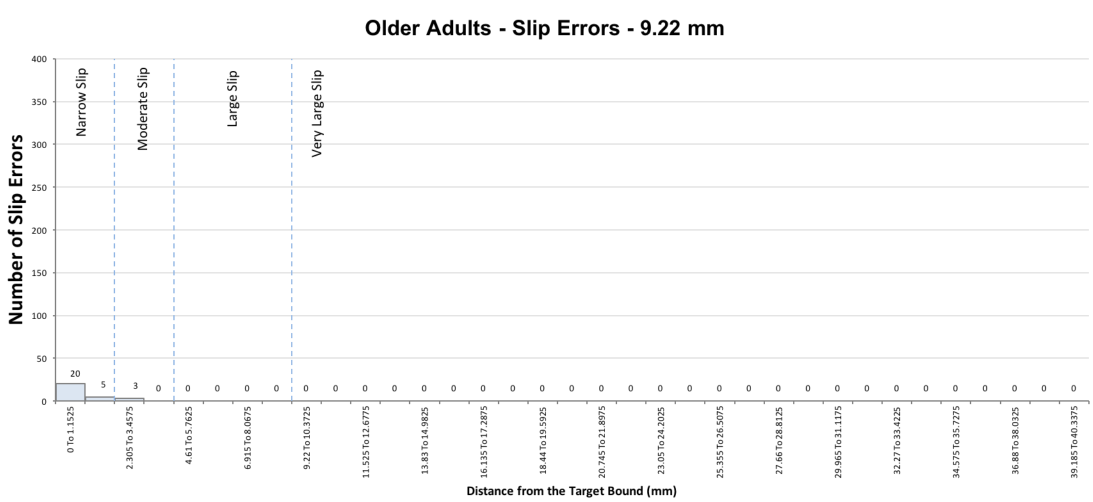


Figure B.15 Histogram of all slip errors for older adults with the largest (9.22mm) targets.

Figure B.16 Histogram of all slip errors for younger adults with the largest (9.22mm) targets.

Appendix C

Additional Results from Finger Trajectory Analysis Study

This appendix includes all additional results from the finger trajectory analysis study that was presented in Chapter 5.

C.1 Overall Performance

This section presents additional results on overall performance that were not included in Chapter 5.

C.1.1 Movement Time

Older adults required significantly longer movement time than younger adults ($F_{1,29} = 39.86, p < .00001, \eta_p^2 = .58$, see Figure C.1). The age-related pairwise performance differences in movement time were also significant across all target widths ($p < .00001$), amplitudes ($p < .00001$) and angles ($p < .00001$).

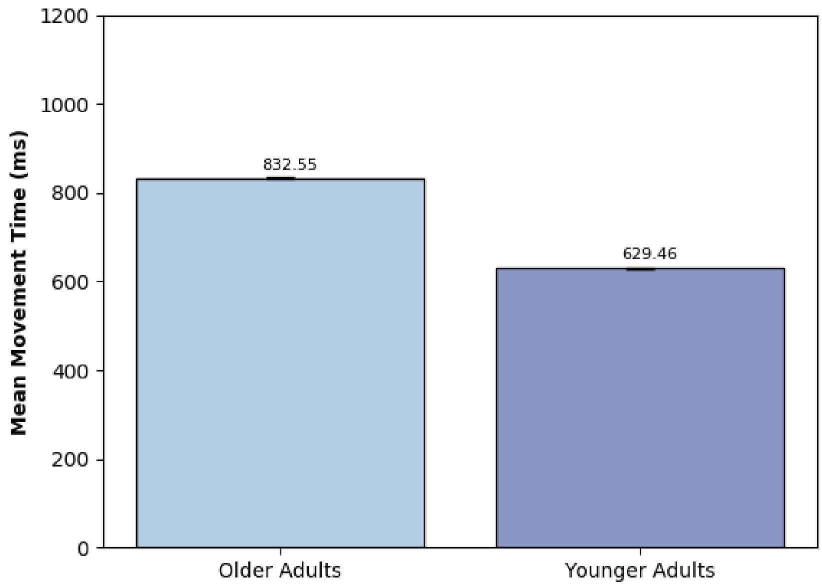


Figure C.1 Mean movement times by age group. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard errors.

Main effect of target width on movement time was significant ($F_{1.63,47.23} = 116.65, p < .00001, \eta_p^2 = .80$, see Figure C.2). Movement times increased as target widths were decreased. Pairwise differences in movement time across target widths were significant ($p < .0001$ for all width pairs). We also observed significant pairwise differences across widths in individual age groups (older adults: $p < .0005$, and younger adults: $p < .005$ for all width pairs).

We also observed significant main effect of target amplitude on movement time ($F_{1.47,42.54} = 285.84, p < .00001, \eta_p^2 = .91$, see Figure C.3), where movement time increased as target amplitude increased (pairwise differences: $p < .00001$ for all pairs). Similar trends were also evident in individual age groups ($p < .00001$ for all amplitude pairs in both older and younger

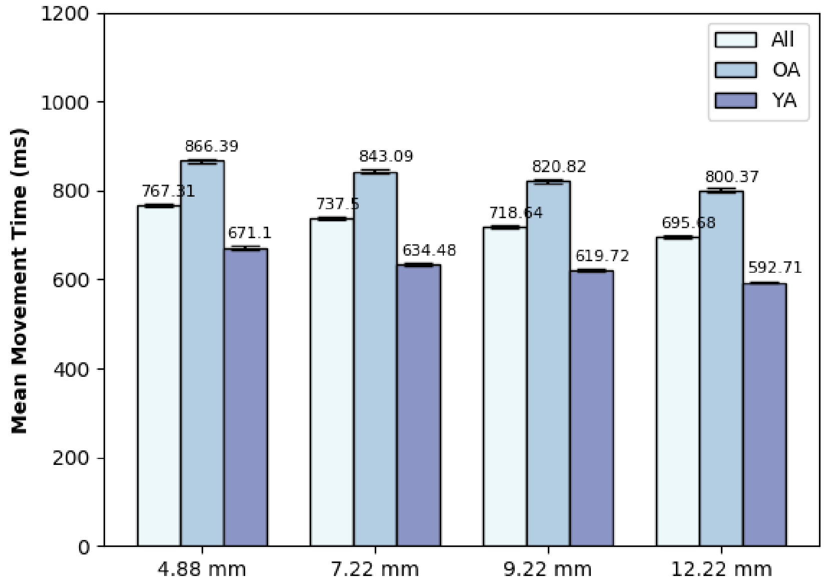


Figure C.2 Mean movement times by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

adults).

Target angle also had significant influence on movement time ($F_{3.95,114.57} = 13.21, p < .00001, \eta_p^2 = .31$, see Figure C.4). For both age groups, targets located at the lower-right corner (315°) were the slowest to select, whereas targets located at the upper-right corner (45°) was the fastest (pairwise difference between 45° and 315° and all angles: $p < .00005$ for older adults and $p < .0005$ for younger adults). These results align with prior work on pen angular movement (Hancock & Booth, 2004), and the error analysis study that was presented in Chapter 3 that right-handed individuals more likely require more time to select targets located at the lower-right corner because of the occlusion caused by the right hand. In addition, older adults needed more time to select the targets located at the lower-right quadrant (0° and 270°), and younger adults needed more time to select the targets located at

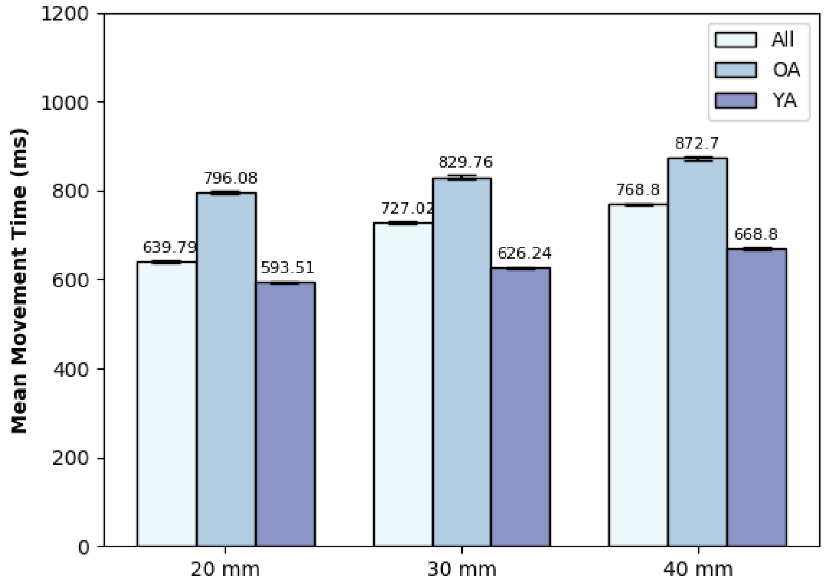


Figure C.3 Mean movement times by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

the upper-left quadrant (90° and 135°). A small interaction effect of age × angle was observed on movement time ($F_{3.95,114.57} = 2.60, p < .05, \eta_p^2 = .08$, see Figure C.5). Movement time for older adults were disproportionately higher than younger adults for the targets located at the bottom of the screen, compared the to targets located at the top of the screen.

C.1.2 Error Rate

Older adults were significantly more error prone than younger adults ($F_{1,29} = 10.61$, $p <.005$, $\eta_p^2 = .27$, see Figure C.6). The pairwise performance differences between age groups were significant across smaller targets only (4.88 mm: $p < .001$, 7.22 mm: $p < .05$, 9.22 mm: $p = 0.099$, 12.22 mm: $p = 0.071$). Pairwise performance differences were significant between age groups across all target amplitudes ($p < .01$) and angles ($p < .05$).

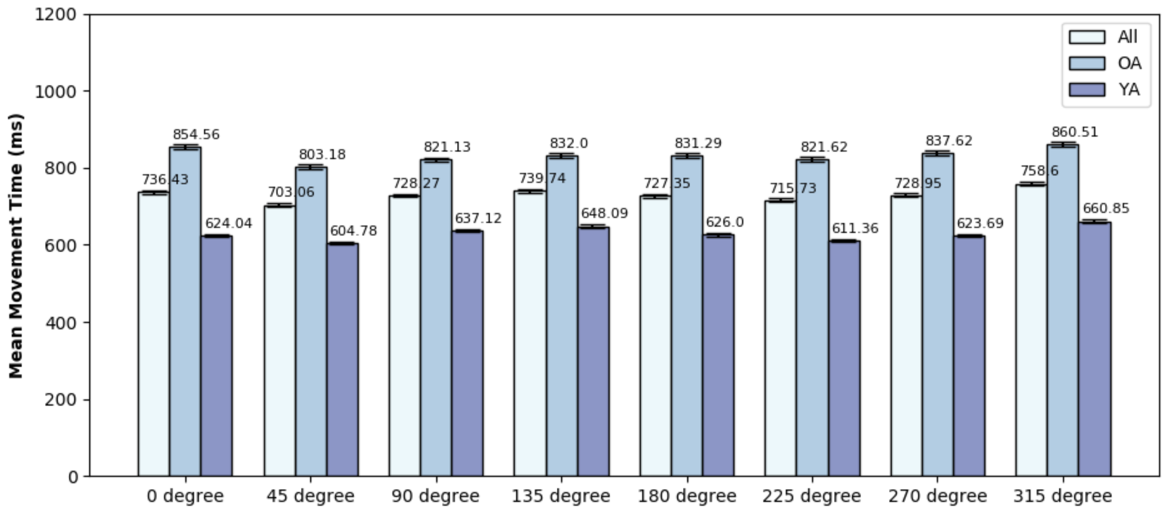


Figure C.4 Mean movement times by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard errors.

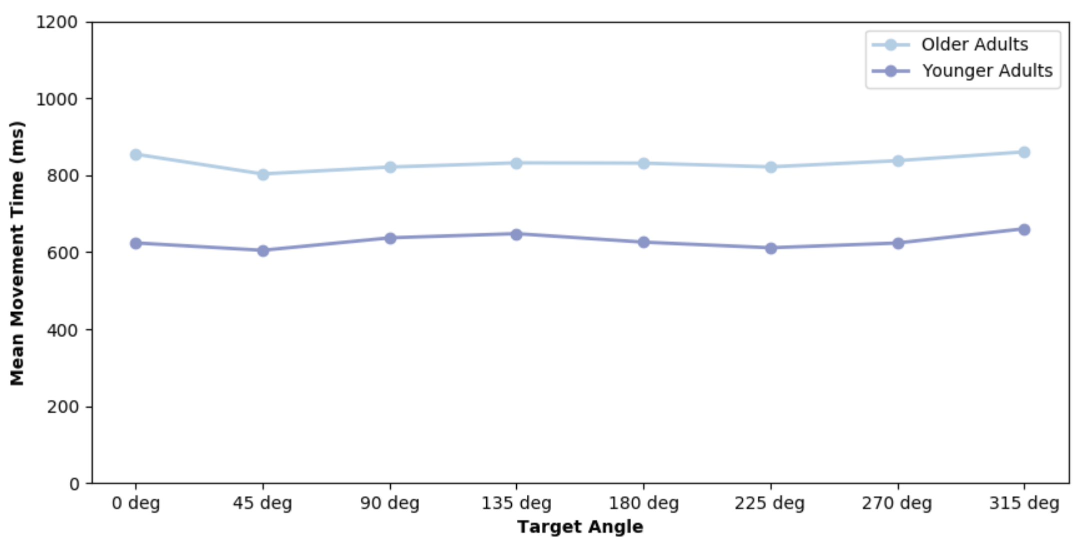


Figure C.5 Interaction effect of age $\times$ angle on mean movement time. For both older and younger adults, $n = 16$.

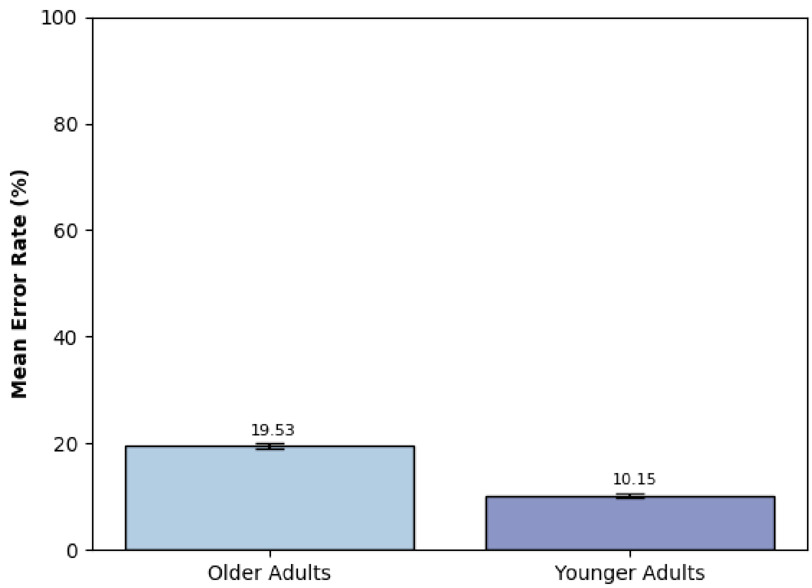


Figure C.6 Mean error rate by age group. For older adults, $n = 16$; for younger adults, $n = 16$. Error bars show the standard error.

Target width had significant main effect on error rates – having decreasing error rates while target widths increased ($F_{1.45,42.09} = 164.97$, $p < .00001$, $\eta_p^2 = .85$, see Figure C.7). Pairwise comparisons were also significant between all width pairs (all participants: $p < .00005$, older adults: $p < .0005$, younger adults: $p < .05$, for all pairs). We also observed strong interaction effect of age × width ($F_{1.45,42.09} = 11.77$, $p < .0005$, $\eta_p^2 = .29$, see Figure C.8). This interaction effect reflects that older adults disproportionately generate more errors with smaller targets, but when target size increases to 12.22 mm, the error rates between older and younger adults becomes comparable from a practical standpoint (older adults: 4.07%, younger adults: 1.71%).

We did not find any main effect of target amplitude ($p = .258$) and target angle ($p = .731$) on error rates.

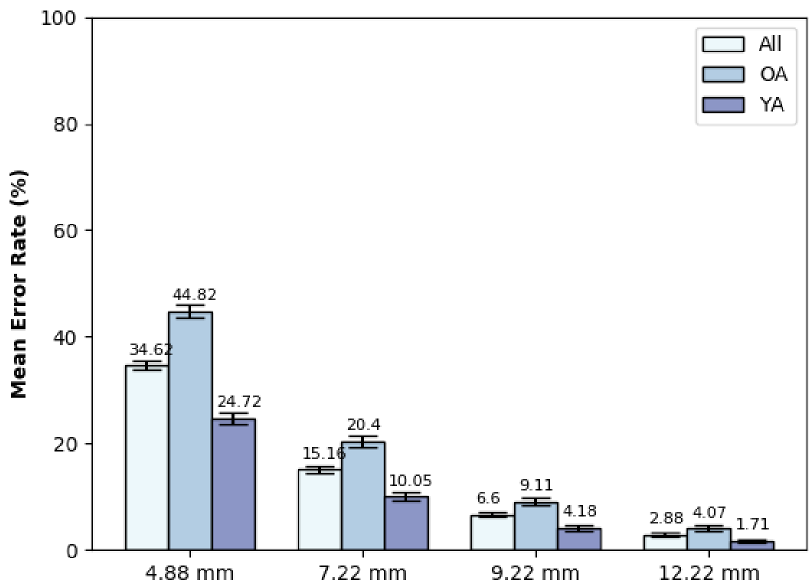


Figure C.7 Mean error rate by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

C.2 Finger Trajectory Measures

This section presents results from the descriptive and inferential statistical analyses on the finger trajectory measures that were not included in Chapter 5. We did not find any significant performance differences in these measures across age groups.

C.2.1 Task Plane Crossing (TPC)

Despite older adults had higher mean task plane crossing (TPC) than that of younger adults, the age-related performance difference was not significant ($p = .218$). Target width also did not have any significant influence on TPC ($p = .825$). However, the main effects of

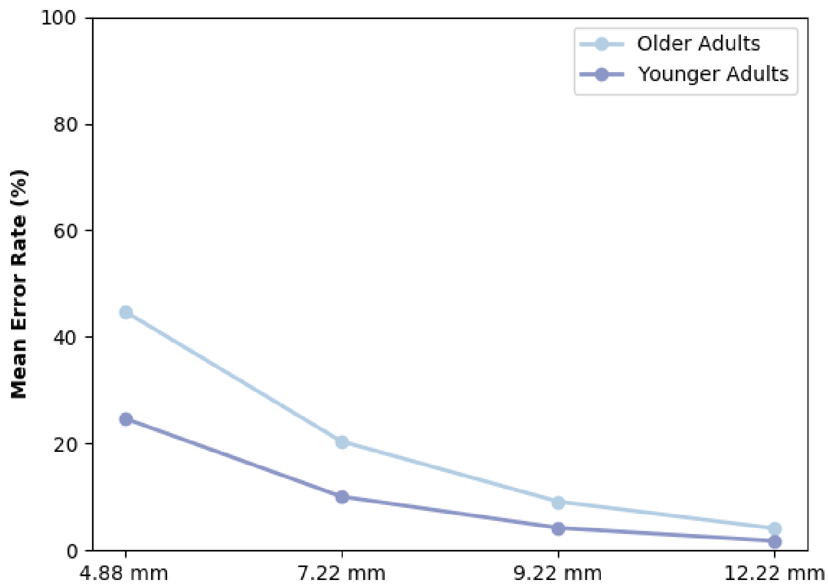


Figure C.8 Interaction effect of age × width on error rates. For both older and younger adults, $n = 16$. While older adults made significantly more errors than younger adults for all target widths, the error rate disproportionately increases for older adults as target size decreases.

both target amplitude ($F_{2,56} = 22.08, p < .00001, \eta_p^2 = .44$, Figure C.9), and target angle ($F_{3.21,89.76} = 325.88, p < .00001, \eta_p^2 = .92$, see Figure C.10) were significant on TPC. Pairwise comparison showed significant differences between all amplitude pairs ($p < .05$ for all pairs). However, for older adults the pairwise differences were significant only for the 20mm-40mm and the 30mm-40mm pairs ($p < .005$ for both pairs). For younger adults, pairwise differences were significant only for the 20mm-30mm and the 20mm-40mm pairs ($p < .0005$ for both pairs).

Targets located at the left side of the screen (135°, 180°, and 225° angles) had very high mean TPCs than targets located at the right side of the screen. The pairwise differences were also significant between the left side and the right side targets ($p < .00001$). Similar

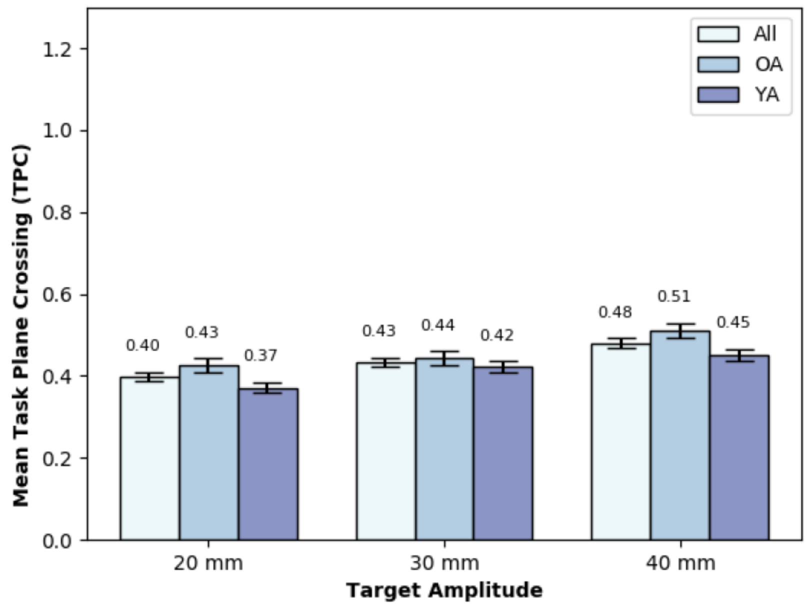


Figure C.9 Mean task plane crossing (TPC) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

trend was visible in both older and younger adults – having significant pairwise differences between the right side and the left side targets.

C.2.2 Movement Offset (MO)

Older adults had lower movement offset (MO) than younger adults, but the age-related performance difference was not significant ($p = .223$). The main effect of target width on MV was also not significant ($p = .068$). Target amplitude had main effect on MO ($F_{1.44,40.26} = 26.53, p < .00001, \eta_p^2 = .49$, see Figure C.11). Unlike other measures, the magnitude (absolute value) of MO decreased as amplitudes increased. Significant pairwise differences between all

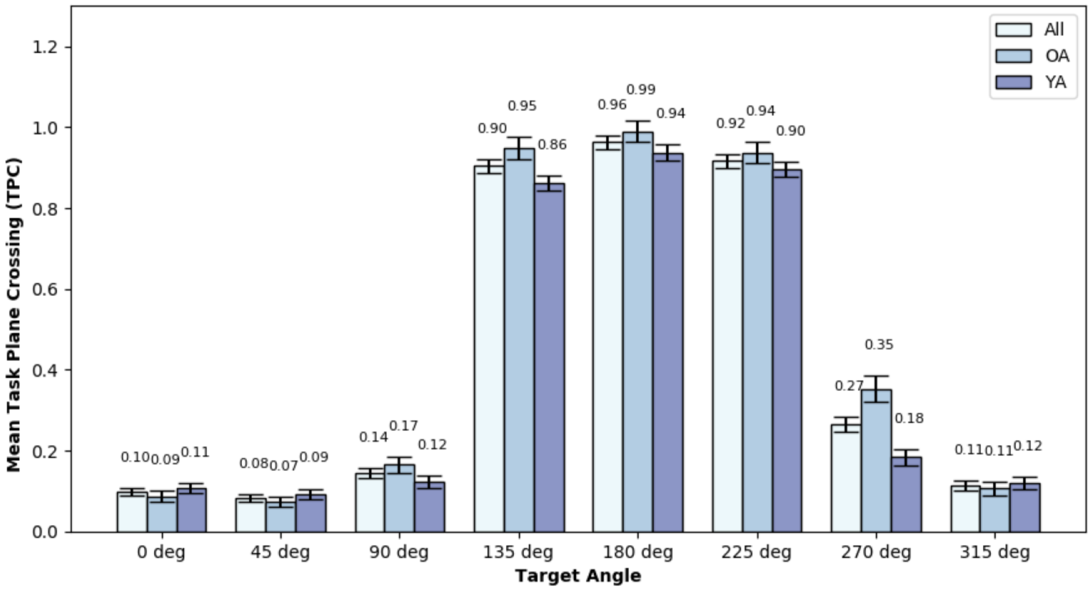


Figure C.10 Mean task plane crossing (TPC) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

amplitude pairs were observed ($p < .01$ for all pairs). Within individual age groups, pairwise differences between amplitudes were also significant ($p < .05$ for all amplitude pairs in both older and younger adults), except for the 20mm-30mm pair for older adults, where the pairwise difference was not significant.

We have observed significant influence of target angle on MO ($F_{1.68,47.00} = 91.91, p < .00001, \eta_p^2 = .77$, see Figure C.12). The mean movement offsets of the targets located at the left side of the screen (135°, 180° and 225°) were significantly ($p < .00001$) lower (in terms of absolute values) than that of the targets located at other locations (Fig. 38). Similar trends in pairwise differences between target angles were found within individual age groups ($p < .00005$ for both age groups). We also observed interaction effect of and amplitude × angle ($F_{6.50,181.97} = 6.33, p < .00001, \eta_p^2 = .18$, see Figure C.13). This interaction effect shows

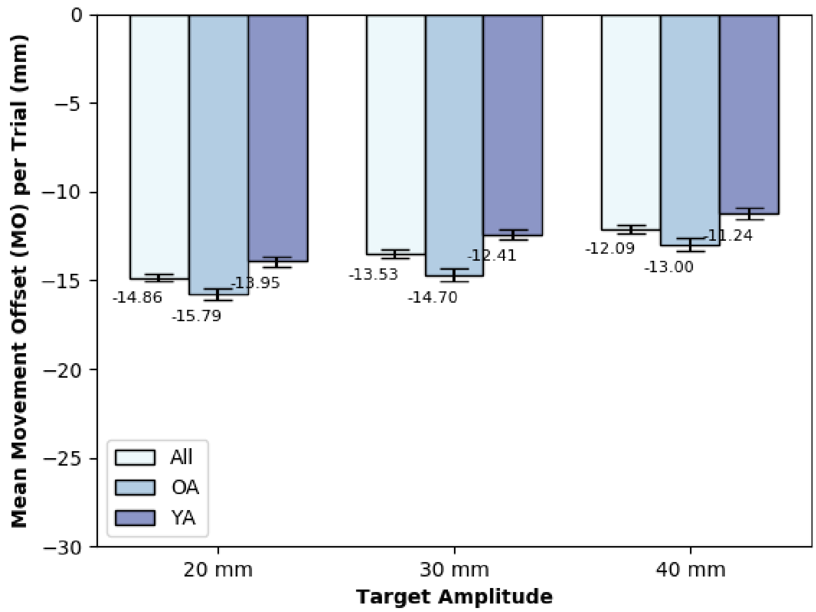


Figure C.11 Mean movement offset (MO) by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

higher performance differences across target amplitudes in the 135°, 180° and 225° locations.

C.2.3 Movement Error (ME)

Our statistical analysis found no significant main or interaction effects of age, target width, amplitude, and angle on movement error (ME).

C.2.4 Pause Frequency (PF)

We did not find any significant main effect of age ($p = .140$), amplitude ($p = .163$), and angle ($p = .113$) on pause frequency (PF). Target width was the only factor that had main effect on PF, ($F_{3,84} = 7.72, p < .0005, \eta_p^2 = .22$, see Figure C.14). The pairwise differences across target widths were significant only for the pairs with the smallest (4.88 mm) targets

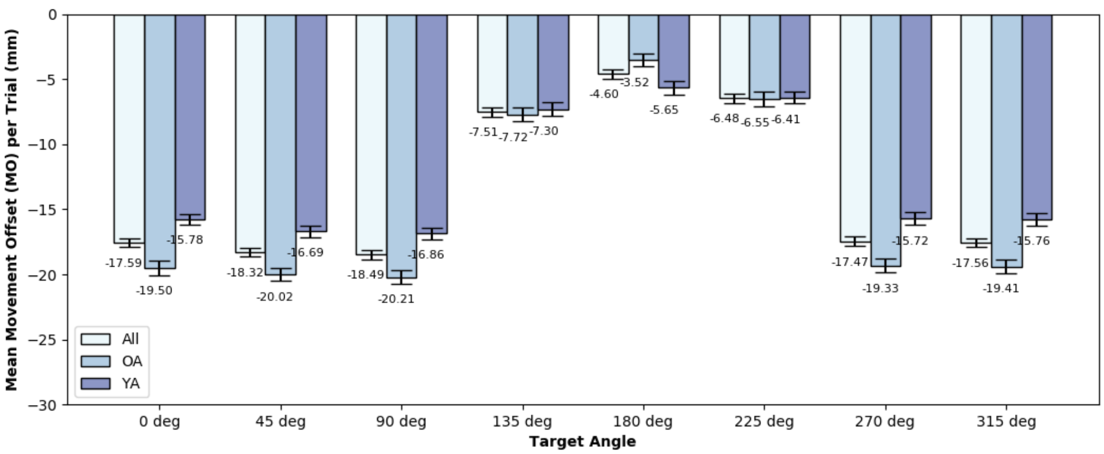


Figure C.12 Mean movement offset (MO) by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

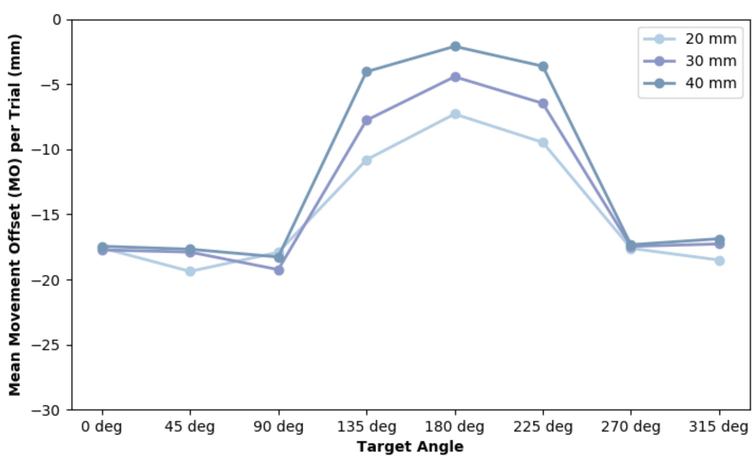


Figure C.13 Interaction effect of amplitude × angle on movement offset (MO). For both older and younger adults, $n = 16$.

(4.88mm-7.22mm: $p < .01$, 4.88mm-9.22mm: $p < .05$, and 4.88mm-12.22mm: $p < .001$). In individual age groups, some pairwise differences with the 4.88 mm targets were significant across widths (older adults: 4.88mm-7.22mm ($p < .005$) and 4.88mm-12.22mm ($p < .005$); younger adults: 4.88mm-9.22mm ($p < .05$) and 4.88mm-12.22mm ($p < .01$). Pairwise differences across other width pairs were not significant.

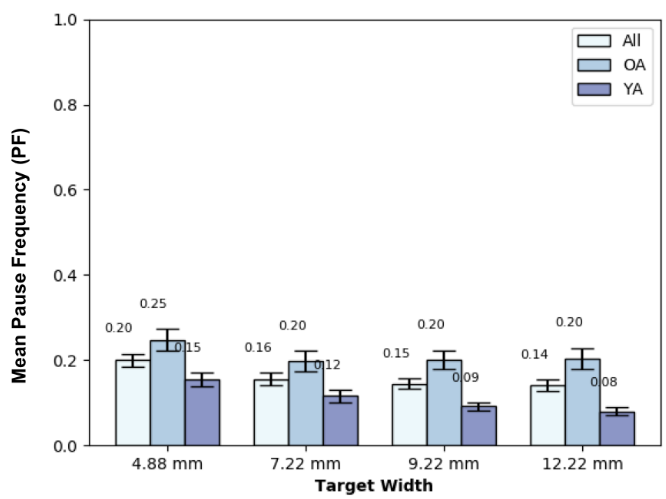


Figure C.14 Mean pauses frequency (PF) per trial by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

C.2.5 Pause Duration (PD)

No significant main effects of age ($p = .211$) or target angles ($p = .278$) were observed on pause duration (PD). However, the main effect of target widths was significant on PD ($F_{2.41,67.49} = 7.35, p < .001, \eta_p^2 = .21$, see Figure C.15). We observed pairwise performance differences between some width pairs containing the smallest targets: 4.88mm-9.22mm ($p <$

.001), and 4.88mm-12.22mm ($p < .0005$). Similar trends were seen in the individual age groups across target widths (older adults: 4.88mm-7.22mm ($p < .05$), 4.88mm-9.22mm ($p < .005$), and 4.88mm-12.22mm ($p < .005$); younger adults: 4.88mm-9.22mm ($p < .05$), and 4.88mm-12.22mm ($p < .005$).

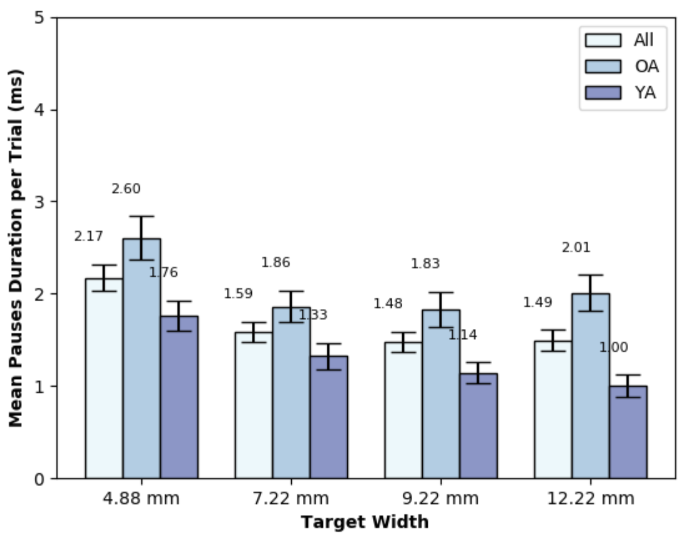


Figure C.15 Mean pause duration (PD) per trial by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Despite significant main effect was observed for target amplitudes ($F_{1.39,38.92} = 3.73, p < .05, \eta_p^2 = .12$, see Figure 5.35), the pairwise performance differences in PD across amplitudes were not significant. Within the older adults, pairwise difference was significant for the target amplitudes that were paired with the 40 mm amplitudes (20 mm: $p < .05$; 30 mm: $p < .005$). Unlike other measures, PD decreased as amplitudes increased for older adults. For younger adults, targets at the 30 mm amplitudes had the lowest PD among all amplitudes, but no significant pairwise differences across amplitudes were observed.

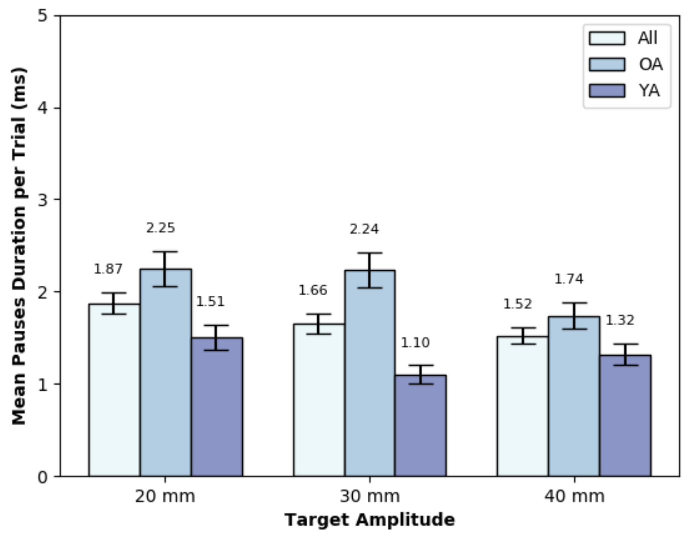


Figure C.16 Mean pause duration (PD) per trial by target amplitudes. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

C.2.6 Mean Speed (SM)

Older adults had higher mean speed (SM) than younger adults, but the performance difference was not significant ($p = .071$). Main effect of width was found on SM ($F_{3,84} = 12.87, p < .00001, \eta_p^2 = .32$, see Figure C.17). Significant pairwise differences were observed for the 4.88mm-9.22mm ($p < .01$), 4.88mm-12.22mm ($p < .0001$), and the 7.22mm-12.22mm ($p < .0005$) width pairs. For older adults, pairwise differences were significant for the following width pairs: 4.88mm-9.22mm ($p < .005$), 4.88mm-12.22mm ($p < .0005$), 7.22mm-9.22mm ($p < .05$), and the 7.22mm-12.22mm ($p < .001$); and for younger adults, pairwise differences were significant only for the width pairs with the 12.22 mm targets: 4.88mm ($p < .005$), 7.22mm ($p < .005$), and 9.22mm ($p < .05$). For both older and younger adults, mean SM increased as target widths increased, unlike most of the other measures.

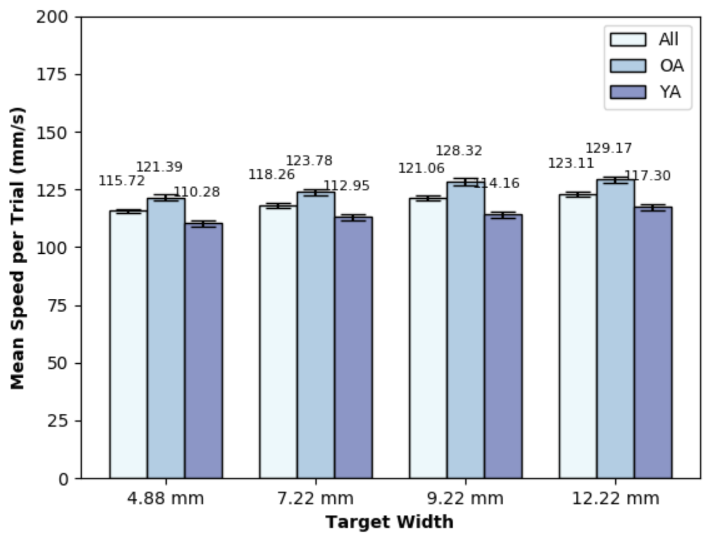


Figure C.17 Mean speed (SM) per trial by target width. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

We also found main effect of target amplitudes on SM ($F2, 56 = 95.70, p < .00001, \eta_p^2 = .77$, see Figure C.18). Pairwise differences were also significant ($p < .00001$) for all pairs. Similar trends in pairwise differences across target amplitudes were observed in individual age groups. We also observed an interaction effects of age × amplitude ($F2, 56 = 4.43, p < .05, \eta_p^2 = .14$, see Figure C.19). This interaction effect reflects that the gaps in SM values between age groups reduce as the amplitude increases.

Target angles also had significant main effect on SM ($F3.24, 90.67 = 30.83, p < .00001, \eta_p^2 = .52$, see Figure C.20). Targets located at the upper-right quadrant (0°, 45°, and 90°) had relatively lower SM than that of targets located at other locations. We also observed pairwise differences between the targets at the upper-right locations and at rest of the screen (0°: 135° ($p < .0005$), 180° ($p < .00001$), 225° ($p < .00001$), 270° ($p < .005$); 45°: 135°

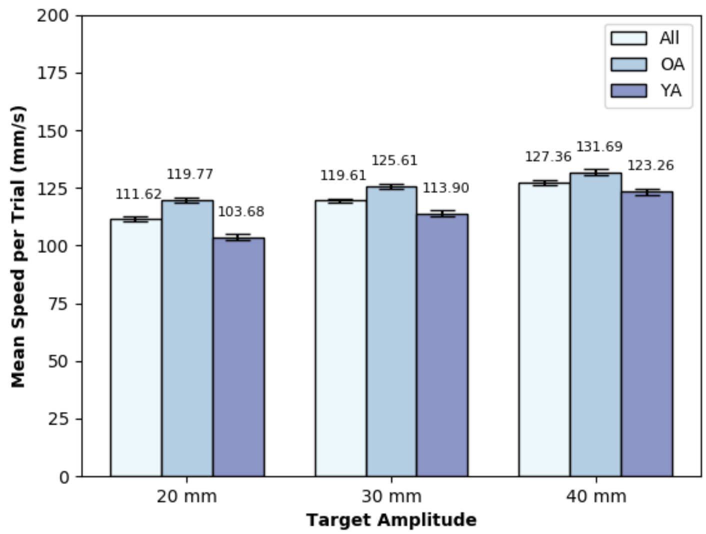


Figure C.18 Mean speed (SM) per trial by target amplitude. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

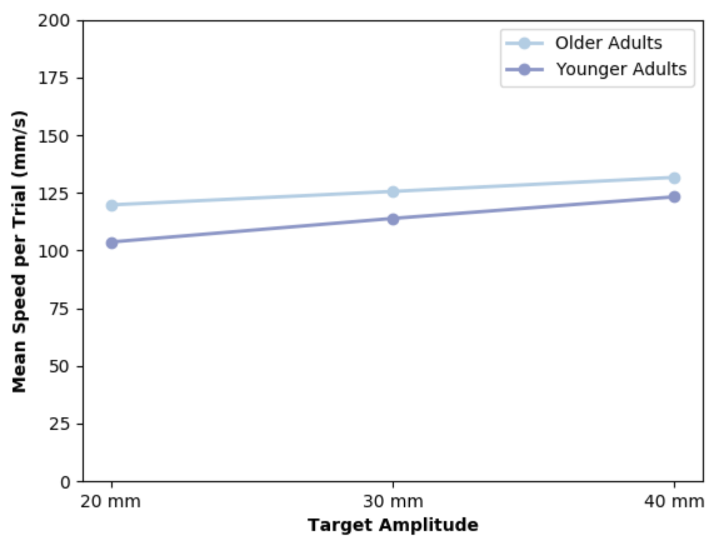


Figure C.19 Interaction effect of age × amplitude on mean speed (SM) per trial. For both older and younger adults, $n = 16$.

($p < .0005$), 180° ($p < .00001$), 225° ($p < .00001$), 270° ($p < .005$); 90°: 135° ($p < .05$), 180° ($p < .0005$), 225° ($p < .00001$)). Similar trends in pairwise differences across target angles were observed within individual age groups. An interaction effect of age × angle was also observed ($F3.24, 90.67 = 6.61, p < .0005, \eta_p^2 = .19$, see Figure C.21). The age × angle interaction effect reflects that older adults had disproportionately higher SM when they selected targets from the bottom half of the screen (225°, 270°, and 315°).

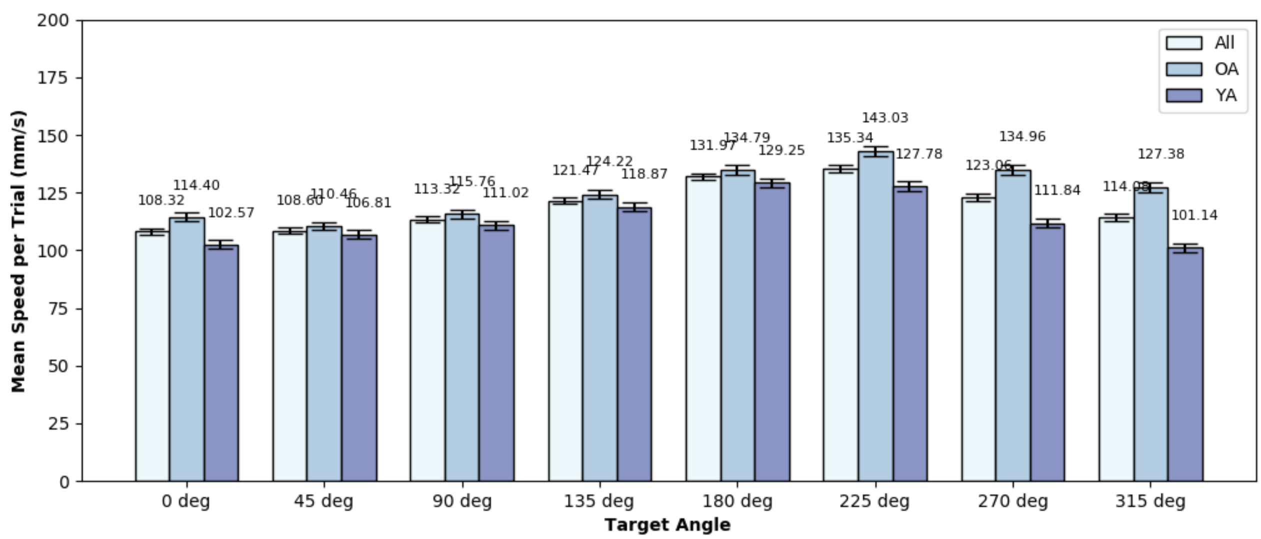


Figure C.20 Mean speed (SM) per trial by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

C.2.7 Mean Yaw (RY)

We did not find any main effect of age ($p = .481$), width ($p = .300$), and amplitude ($p = .354$) on mean yaw (RY) per trial. The only main effect we observed was for target angles ($F_{4.17,116.64} = 4.49, p < .005, \eta_p^2 = .14$, see Figure C.22). The RY was slightly higher (the absolute values) for the targets located at the left side of the screen (135°, 180°, and 225°).

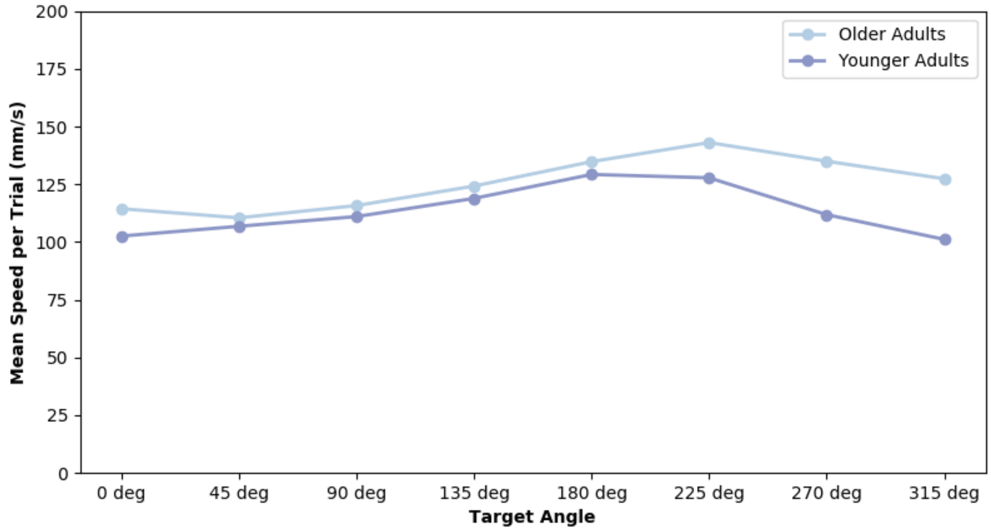


Figure C.21 Interaction effect of age × angle on mean speed (SM) per trial. For both older and younger adults, $n = 16$.

Pairwise analysis found significant differences in some of these pairs (135°: 0° ($p < .005$), 45° ($p < .01$), 225°: 0° ($p < .05$), 45° ($p < .05$)). The following pairwise differences between the right side and the left side angles were significant within individual age groups, for older adults: 135° (0° and 45° ($p < .005$ for both)), 180° (0° ($p < .05$), 45° ($p < .0005$)), 135° (0° ($p < .005$) and 45° ($p < .005$), 90° ($p < .05$)); for younger adults: 135° (0° and 45° ($p < .05$ for both)).

C.2.8 Mean Pitch (RP)

We did not find any main effect of age ($p = .145$), width ($p = .648$), and amplitude ($p = .328$) on mean pitch (RP) per trial. The only significant main effect on RP was observed for target angles ($F_{4.00,112.07} = 9.88, p < .00001, \eta_p^2 = .26$, see Figure C.23). Targets that were located at the bottom of the screen (225°, 270°, and 315°) had higher RP than targets that were

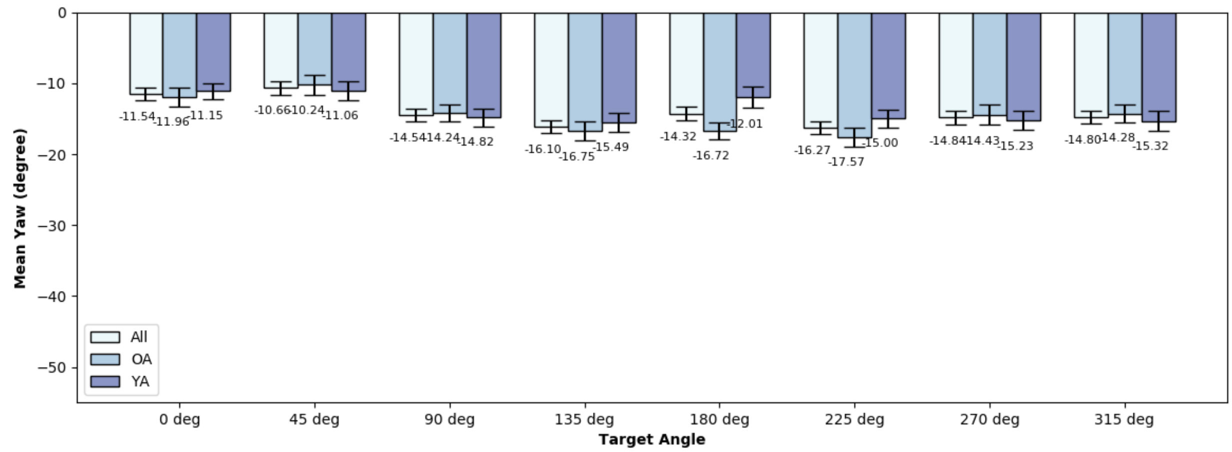


Figure C.22 Mean yaw (RY) per trial by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

located at the top of the screen. Pairwise analysis found significant differences in some top and bottom angle pairs: (225°: 45° ($p < .05$), 90° ($p < .005$), 135° ($p < .005$); 270°: 0° ($p < .05$), 45° ($p < .00005$), 90° ($p < .00005$), 135° ($p < .00005$), 180° ($p < .0005$); 315°: 90° ($p < .01$), 135° ($p < .0005$)). Similar trends in pairwise comparison across target angles were observed within individual age groups.

C.3 Inferential Statistics from Finger Trajectory Analysis Study

We present all inferential statistics from the finger trajectory analysis study from Chapter 5 in this section (see Tables C.1 - C.18). All main and interaction effects reported here are from repeated measure ANOVAs having target width, amplitude and angle as within subject and age as between subject factors. All pairwise comparisons were corrected with a Bonferroni correction. Mauchly's test was conducted to identify sphericity violations and corrected with

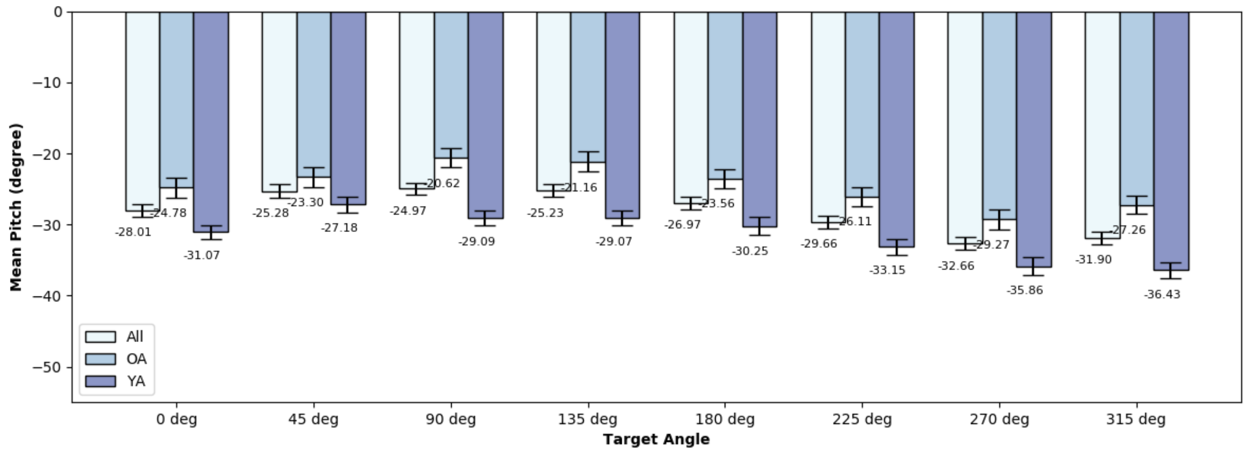


Figure C.23 Mean pitch (RP) per trial by target angle. For all participants (All), $N = 32$; for older adults (OA), $n = 16$; for younger adults (YA), $n = 16$. Error bars show the standard error.

Greenhouse-Geisser corrections; where degrees of freedom (*df*) are non-integer, a correction has been applied.

Table C.1 Statistical Inference from Movement Time (MT)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,29} = 39.86$	$p < .00001$	$\eta_p^2 = .58$
Width	$F_{1.63,47.23} = 116.65$	$p < .00001$	$\eta_p^2 = .80$
Amplitude	$F_{1.47,42.54} = 285.84$	$p < .00001$	$\eta_p^2 = .91$
Angle	$F_{3.95,114.57} = 13.21$	$p < .00001$	$\eta_p^2 = .31$
Age × Width	$F_{1.63,47.23} = 0.65$	$p = .494$	$\eta_p^2 = .02$
Age × Amplitude	$F_{1.47,42.54} = 0.21$	$p = .930$	$\eta_p^2 = .01$
Age × Angle	$F_{3.95,114.57} = 2.60$	$p < .05$	$\eta_p^2 = .08$
Age × Width × Amplitude	$F_{4.47,129.53} = 0.63$	$p = .661$	$\eta_p^2 = .02$
Age × Width × Angle	$F_{9.59,278.20} = 0.55$	$p = .846$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{6.74,195.42} = 1.06$	$p = .393$	$\eta_p^2 = .04$
Age × Width × Amplitude × Angle	$F_{42,1218} = 1.06$	$p = .364$	$\eta_p^2 = .04$
Width × Amplitude	$F_{4.47,129.53} = 2.29$	$p = .056$	$\eta_p^2 = .07$
Width × Angle	$F_{9.59,278.20} = 1.06$	$p = .395$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{6.74,195.42} = 3.81$	$p < .001$	$\eta_p^2 = .12$
Width × Amplitude × Angle	$F_{42,1218} = 1.16$	$p = .225$	$\eta_p^2 = .04$

Table C.2 Statistical Inference from Error Rate

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,29} = 10.61$	$p < .005$	$\eta_p^2 = .27$
Width	$F_{1.45,42.09} = 164.97$	$p < .00001$	$\eta_p^2 = .85$
Amplitude	$F_{2,58} = 1.39$	$p = .258$	$\eta_p^2 = .05$
Angle	$F_{4.07,118.03} = 0.51$	$p = .731$	$\eta_p^2 = .02$
Age × Width	$F_{1.45,42.09} = 11.77$	$p < .0005$	$\eta_p^2 = .29$
Age × Amplitude	$F_{2,58} = 0.07$	$p = .936$	$\eta_p^2 = .002$
Age × Angle	$F_{4.07,118.03} = 1.51$	$p = .204$	$\eta_p^2 = .05$
Age × Width × Amplitude	$F_{4.04,117.21} = 0.29$	$p = .885$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{9.65,279.88} = 0.89$	$p = .544$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{14,406} = 0.93$	$p = .523$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1218} = 1.17$	$p = .209$	$\eta_p^2 = .04$
Width × Amplitude	$F_{4.04,117.21} = 1.54$	$p = .195$	$\eta_p^2 = .05$
Width × Angle	$F_{9.65,279.88} = 1.70$	$p < .1$	$\eta_p^2 = .06$
Amplitude × Angle	$F_{14,406} = 1.93$	$p < .05$	$\eta_p^2 = .06$
Width × Amplitude × Angle	$F_{42,1218} = 0.94$	$p = .581$	$\eta_p^2 = .03$

Table C.3 Statistical Inference from Movement Direction Change in X-direction (DC-X)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 8.99$	$p < .01$	$\eta_p^2 = .24$
Width	$F_{2.56,71.27} = 7.55$	$p < .0005$	$\eta_p^2 = .21$
Amplitude	$F_{2,56} = 42.87$	$p < .00001$	$\eta_p^2 = .61$
Angle	$F_{4.41,123.44} = 57.15$	$p < .00001$	$\eta_p^2 = .67$
Age × Width	$F_{2.56,71.27} = 0.91$	$p = .430$	$\eta_p^2 = .03$
Age × Amplitude	$F_{2,56} = 0.18$	$p = .838$	$\eta_p^2 = .01$
Age × Angle	$F_{4.41,123.44} = 1.44$	$p = .220$	$\eta_p^2 = .05$
Age × Width × Amplitude	$F_{6,168} = 2.71$	$p < .05$	$\eta_p^2 = .09$
Age × Width × Angle	$F_{9.58,268.32} = 0.51$	$p = .874$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{6.37,178.27} = 2.50$	$p < .05$	$\eta_p^2 = .08$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.08$	$p = .340$	$\eta_p^2 = .04$
Width × Amplitude	$F_{6,168} = 2.03$	$p < .1$	$\eta_p^2 = .07$
Width × Angle	$F_{9.58,268.32} = 0.91$	$p = .522$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{6.37,178.27} = 7.04$	$p < .00001$	$\eta_p^2 = .20$
Width × Amplitude × Angle	$F_{42,1176} = 0.67$	$p = .950$	$\eta_p^2 = .02$

Table C.4 Statistical Inference from Direction Changes along y-axis (DC-Y)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 20.39$	$p < .0005$	$\eta_p^2 = .42$
Width	$F_{2.16,60.40} = 6.32$	$p < .005$	$\eta_p^2 = .18$
Amplitude	$F_{1.67,46.76} = 9.70$	$p < .001$	$\eta_p^2 = .26$
Angle	$F_{4.48,125.36} = 7.81$	$p < .00001$	$\eta_p^2 = .22$
Age × Width	$F_{2.16,60.40} = 1.75$	$p = .180$	$\eta_p^2 = .06$
Age × Amplitude	$F_{1.67,46.76} = 0.84$	$p = .421$	$\eta_p^2 = .03$
Age × Angle	$F_{4.48,125.36} = 11.81$	$p < .00001$	$\eta_p^2 = .30$
Age × Width × Amplitude	$F_{4.11,115.10} = 1.24$	$p = .297$	$\eta_p^2 = .04$
Age × Width × Angle	$F_{9.85,275.85} = 1.18$	$p = .304$	$\eta_p^2 = .04$
Age × Amplitude × Angle	$F_{6.89,192.79} = 1.21$	$p = .299$	$\eta_p^2 = .04$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.41$	$p = .249$	$\eta_p^2 = .04$
Width × Amplitude	$F_{4.11,115.10} = 0.74$	$p = .569$	$\eta_p^2 = .03$
Width × Angle	$F_{9.85,275.85} = 0.88$	$p = .555$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{6.89,192.79} = 2.31$	$p < .05$	$\eta_p^2 = .08$
Width × Amplitude × Angle	$F_{42,1176} = 1.20$	$p = .186$	$\eta_p^2 = .04$

Table C.5 Statistical Inference from Movement Direction Changes along z-axis (DC-Z)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 30.21$	$p < .00001$	$\eta_p^2 = .52$
Width	$F_{2.43,67.93} = 3.70$	$p < .05$	$\eta_p^2 = .12$
Amplitude	$F_{2,56} = 20.47$	$p < .00001$	$\eta_p^2 = .42$
Angle	$F_{4.82,134.82} = 24.66$	$p < .00001$	$\eta_p^2 = .47$
Age × Width	$F_{2.43,67.93} = 3.34$	$p < .05$	$\eta_p^2 = .11$
Age × Amplitude	$F_{2,56} = 0.70$	$p = .502$	$\eta_p^2 = .02$
Age × Angle	$F_{4.82,134.82} = 5.90$	$p < .0001$	$\eta_p^2 = .17$
Age × Width × Amplitude	$F_{6,168} = 1.15$	$p = .338$	$\eta_p^2 = .04$
Age × Width × Angle	$F_{10.14,283.85} = 0.94$	$p = .499$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{8.02,224.64} = 1.40$	$p = .199$	$\eta_p^2 = .05$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.33$	$p < .1$	$\eta_p^2 = .05$
Width × Amplitude	$F_{6,168} = 1.40$	$p = .219$	$\eta_p^2 = .05$
Width × Angle	$F_{10.14,283.85} = 0.58$	$p = .834$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{8.02,224.64} = 3.24$	$p < .005$	$\eta_p^2 = .10$
Width × Amplitude × Angle	$F_{42,1176} = 1.08$	$p = .336$	$\eta_p^2 = .04$

Table C.6 Statistical Inference from Number of Task Plane Crossing (TPC)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 1.59$	$p = .218$	$\eta_p^2 = .05$
Width	$F_{3,84} = 0.30$	$p = .825$	$\eta_p^2 = .01$
Amplitude	$F_{2,56} = 22.08$	$p < .00001$	$\eta_p^2 = .44$
Angle	$F_{3.21,89.76} = 325.88$	$p < .00001$	$\eta_p^2 = .92$
Age × Width	$F_{3,84} = 0.44$	$p = .727$	$\eta_p^2 = .02$
Age × Amplitude	$F_{2,56} = 2.04$	$p = .140$	$\eta_p^2 = .07$
Age × Angle	$F_{3.21,89.76} = 2.52$	$p < .1$	$\eta_p^2 = .08$
Age × Width × Amplitude	$F_{6,168} = 1.50$	$p = .182$	$\eta_p^2 = .05$
Age × Width × Angle	$F_{9.87,276.21} = 0.94$	$p = .494$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{6.91,193.47} = 1.14$	$p = .342$	$\eta_p^2 = .04$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.34$	$p < .1$	$\eta_p^2 = .05$
Width × Amplitude	$F_{6,168} = 0.88$	$p = .509$	$\eta_p^2 = .03$
Width × Angle	$F_{9.87,276.21} = 0.80$	$p = .630$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{6.91,193.47} = 1.18$	$p = .315$	$\eta_p^2 = .04$
Width × Amplitude × Angle	$F_{42,1176} = 0.67$	$p = .951$	$\eta_p^2 = .02$

Table C.7 Statistical Inference from Movement Variability (MV)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 6.57$	$p < .05$	$\eta_p^2 = .19$
Width	$F_{2.53,65.88} = 0.37$	$p = .730$	$\eta_p^2 = .01$
Amplitude	$F_{1.67,46.86} = 45.33$	$p < .00001$	$\eta_p^2 = .62$
Angle	$F_{1.24,34.79} = 72.44$	$p < .00001$	$\eta_p^2 = .72$
Age × Width	$F_{2.53,65.88} = 0.36$	$p = .734$	$\eta_p^2 = .01$
Age × Amplitude	$F_{1.67,46.86} = 2.02$	$p = .151$	$\eta_p^2 = .07$
Age × Angle	$F_{1.24,34.79} = 0.16$	$p = .744$	$\eta_p^2 = .01$
Age × Width × Amplitude	$F_{6,168} = 0.79$	$p = .577$	$\eta_p^2 = .03$
Age × Width × Angle	$F_{10.01,280.20} = 1.03$	$p = .417$	$\eta_p^2 = .04$
Age × Amplitude × Angle	$F_{7.67,214.63} = 0.76$	$p = .637$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 0.89$	$p = .672$	$\eta_p^2 = .03$
Width × Amplitude	$F_{6,168} = 0.61$	$p = .724$	$\eta_p^2 = .02$
Width × Angle	$F_{10.01,280.20} = 0.48$	$p = .904$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{7.67,214.63} = 3.75$	$p < .0005$	$\eta_p^2 = .12$
Width × Amplitude × Angle	$F_{42,1176} = 1.09$	$p = .323$	$\eta_p^2 = .04$

Table C.8 Statistical Inference from Movement Offset (MO)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 1.55$	$p = .223$	$\eta_p^2 = .05$
Width	$F_{3,84} = 2.47$	$p < .1$	$\eta_p^2 = .08$
Amplitude	$F_{1.44,40.26} = 26.53$	$p < .00001$	$\eta_p^2 = .49$
Angle	$F_{1.68,47.00} = 91.91$	$p < .00001$	$\eta_p^2 = .77$
Age × Width	$F_{3,84} = 0.09$	$p = .964$	$\eta_p^2 = .003$
Age × Amplitude	$F_{1.44,40.26} = 0.17$	$p = .774$	$\eta_p^2 = .01$
Age × Angle	$F_{1.68,47.00} = 2.99$	$p < .1$	$\eta_p^2 = .10$
Age × Width × Amplitude	$F_{6,168} = 0.29$	$p = .940$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{9.43,263.91} = 0.52$	$p = .866$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{6.50,181.97} = 1.49$	$p = .180$	$\eta_p^2 = .05$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.22$	$p = .161$	$\eta_p^2 = .04$
Width × Amplitude	$F_{6,168} = 1.12$	$p = .351$	$\eta_p^2 = .04$
Width × Angle	$F_{9.43,263.91} = 1.17$	$p = .316$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{6.50,181.97} = 6.33$	$p < .00001$	$\eta_p^2 = .18$
Width × Amplitude × Angle	$F_{42,1176} = 0.88$	$p = .692$	$\eta_p^2 = .03$

Table C.9 Statistical Inference from Movement Error (ME)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 1.75$	$p = .197$	$\eta_p^2 = .06$
Width	$F_{3,84} = 1.05$	$p = .374$	$\eta_p^2 = .04$
Amplitude	$F_{1.69,47.25} = 0.64$	$p = .507$	$\eta_p^2 = .02$
Angle	$F_{4.90,137.28} = 1.64$	$p = .156$	$\eta_p^2 = .06$
Age × Width	$F_{3,84} = 0.70$	$p = .555$	$\eta_p^2 = .02$
Age × Amplitude	$F_{1.69,47.25} = 0.61$	$p = .521$	$\eta_p^2 = .02$
Age × Angle	$F_{4.90,137.28} = 0.61$	$p = .687$	$\eta_p^2 = .02$
Age × Width × Amplitude	$F_{6,168} = 0.33$	$p = .920$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{9.59,268.44} = 0.98$	$p = .459$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{8.32,232.83} = 0.93$	$p = .497$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 0.71$	$p = .919$	$\eta_p^2 = .03$
Width × Amplitude	$F_{6,168} = 1.52$	$p = .173$	$\eta_p^2 = .05$
Width × Angle	$F_{9.59,268.44} = 1.01$	$p = .433$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{8.32,232.83} = 0.71$	$p = .692$	$\eta_p^2 = .03$
Width × Amplitude × Angle	$F_{42,1176} = 0.94$	$p = .575$	$\eta_p^2 = .03$

Table C.10 Statistical Inference from Pause Frequency (PF)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 2.30$	$p = .140$	$\eta_p^2 = .08$
Width	$F_{3,84} = 7.72$	$p < .0005$	$\eta_p^2 = .22$
Amplitude	$F_{1.53,42.81} = 1.95$	$p = .163$	$\eta_p^2 = .07$
Angle	$F_{4.49,125.84} = 1.86$	$p = .113$	$\eta_p^2 = .06$
Age × Width	$F_{3,84} = 0.48$	$p = .699$	$\eta_p^2 = .02$
Age × Amplitude	$F_{1.53,42.81} = 1.49$	$p = .236$	$\eta_p^2 = .05$
Age × Angle	$F_{4.49,125.84} = 0.97$	$p = .432$	$\eta_p^2 = .03$
Age × Width × Amplitude	$F_{2.57,71.96} = 0.33$	$p = .773$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{4.15,116.08} = 0.72$	$p = .582$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{4.31,120.64} = 0.97$	$p = .434$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.02$	$p = .434$	$\eta_p^2 = .04$
Width × Amplitude	$F_{2.57,71.96} = 0.48$	$p = .671$	$\eta_p^2 = .02$
Width × Angle	$F_{4.15,116.08} = 1.11$	$p = .357$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{4.31,120.64} = 1.54$	$p = .190$	$\eta_p^2 = .05$
Width × Amplitude × Angle	$F_{42,1176} = 1.00$	$p = .471$	$\eta_p^2 = .04$

Table C.11 Statistical Inference from Pause Duration (PD)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 1.64$	$p = .211$	$\eta_p^2 = .08$
Width	$F_{2.41,67.49} = 7.35$	$p < .001$	$\eta_p^2 = .21$
Amplitude	$F_{1.39,38.92} = 3.73$	$p < .05$	$\eta_p^2 = .12$
Angle	$F_{4.82,134.84} = 1.28$	$p = .278$	$\eta_p^2 = .04$
Age × Width	$F_{2.41,67.49} = 0.50$	$p = .641$	$\eta_p^2 = .02$
Age × Amplitude	$F_{1.39,38.92} = 1.95$	$p = .166$	$\eta_p^2 = .07$
Age × Angle	$F_{4.82,134.84} = 1.14$	$p = .344$	$\eta_p^2 = .04$
Age × Width × Amplitude	$F_{3.61,101.20} = 0.21$	$p = .919$	$\eta_p^2 = .01$
Age × Width × Angle	$F_{6.41,179.38} = 1.14$	$p = .340$	$\eta_p^2 = .04$
Age × Amplitude × Angle	$F_{5.50,153.90} = 0.92$	$p = .474$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.04$	$p = .396$	$\eta_p^2 = .04$
Width × Amplitude	$F_{3.61,101.20} = 0.53$	$p = .695$	$\eta_p^2 = .02$
Width × Angle	$F_{6.41,179.38} = 1.06$	$p = .392$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{5.50,153.90} = 2.16$	$p < .1$	$\eta_p^2 = .07$
Width × Amplitude × Angle	$F_{42,1176} = 1.14$	$p = .250$	$\eta_p^2 = .04$

Table C.12 Statistical Inference from Pause Location Distance (PLD)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 4.26$	$p < .05$	$\eta_p^2 = .13$
Width	$F_{3,84} = 4.43$	$p < .01$	$\eta_p^2 = .14$
Amplitude	$F_{2,56} = 1.52$	$p = .228$	$\eta_p^2 = .05$
Angle	$F_{F5.07,142.01} = 5.38$	$p < .0005$	$\eta_p^2 = .16$
Age × Width	$F_{3,84} = 1.00$	$p = .396$	$\eta_p^2 = .04$
Age × Amplitude	$F_{2,56} = 0.72$	$p = .491$	$\eta_p^2 = .03$
Age × Angle	$F_{5.07,142.01} = 1.32$	$p = .260$	$\eta_p^2 = .05$
Age × Width × Amplitude	$F_{6,168} = 0.69$	$p = .660$	$\eta_p^2 = .02$
Age × Width × Angle	$F_{10.59,296.57} = 0.76$	$p = .678$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{8.13,227.59} = 0.73$	$p = .669$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.21$	$p = .277$	$\eta_p^2 = .04$
Width × Amplitude	$F_{6,168} = 0.69$	$p = .656$	$\eta_p^2 = .02$
Width × Angle	$F_{10.59,296.57} = 0.90$	$p = .537$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{8.13,227.59} = 1.76$	$p < .1$	$\eta_p^2 = .06$
Width × Amplitude × Angle	$F_{42,1176} = 1.06$	$p = .364$	$\eta_p^2 = .04$

Table C.13 Statistical Inference from Path Axis Ratio (PAR)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 29.40$	$p < .00001$	$\eta_p^2 = .51$
Width	$F_{2.45,68.55} = 1.21$	$p = .309$	$\eta_p^2 = .04$
Amplitude	$F_{1.44,40.20} = 149.24$	$p < .00001$	$\eta_p^2 = .84$
Angle	$F_{4.09,114.60} = 43.70$	$p < .00001$	$\eta_p^2 = .61$
Age × Width	$F_{2.45,68.55} = 0.94$	$p = .413$	$\eta_p^2 = .03$
Age × Amplitude	$F_{1.44,40.20} = 26.47$	$p < .00001$	$\eta_p^2 = .49$
Age × Angle	$F_{4.09,114.60} = 3.67$	$p < .01$	$\eta_p^2 = .12$
Age × Width × Amplitude	$F_{6,168} = 0.92$	$p = .480$	$\eta_p^2 = .03$
Age × Width × Angle	$F_{8.19,229.23} = 0.86$	$p = .551$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{7.43,207.96} = 0.79$	$p = .606$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 0.89$	$p = .627$	$\eta_p^2 = .03$
Width × Amplitude	$F_{6,168} = 0.29$	$p = .941$	$\eta_p^2 = .01$
Width × Angle	$F_{8.19,229.23} = 1.01$	$p = .429$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{7.43,207.96} = 1.72$	$p = .102$	$\eta_p^2 = .06$
Width × Amplitude × Angle	$F_{42,1176} = 1.07$	$p = .362$	$\eta_p^2 = .04$

Table C.14 Statistical Inference from Peak Speed (SP)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 7.71$	$p < .01$	$\eta_p^2 = .22$
Width	$F_{3,84} = 0.52$	$p = .672$	$\eta_p^2 = .02$
Amplitude	$F_{1.60,44.81} = 36.77$	$p < .00001$	$\eta_p^2 = .57$
Angle	$F_{7,196} = 7.20$	$p < .00001$	$\eta_p^2 = .21$
Age × Width	$F_{3,84} = 0.36$	$p = .785$	$\eta_p^2 = .01$
Age × Amplitude	$F_{1.60,44.81} = 1.20$	$p = .303$	$\eta_p^2 = .04$
Age × Angle	$F_{7,196} = 4.13$	$p < .0005$	$\eta_p^2 = .13$
Age × Width × Amplitude	$F_{6,168} = 1.01$	$p = .421$	$\eta_p^2 = .04$
Age × Width × Angle	$F_{7.16,200.39} = 1.10$	$p = .366$	$\eta_p^2 = .04$
Age × Amplitude × Angle	$F_{7.07,197.97} = 0.51$	$p = .830$	$\eta_p^2 = .02$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.05$	$p = .379$	$\eta_p^2 = .04$
Width × Amplitude	$F_{6,168} = 0.48$	$p = .824$	$\eta_p^2 = .02$
Width × Angle	$F_{7.16,200.39} = 0.55$	$p = .798$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{7.07,197.97} = 0.73$	$p = .648$	$\eta_p^2 = .03$
Width × Amplitude × Angle	$F_{42,1176} = 0.81$	$p = .809$	$\eta_p^2 = .03$

Table C.15 Statistical Inference from Mean Speed (SM)

Factor	**F-Statistics**	**Significance**	**Effect Size**
Age	$F_{1,28} = 3.52$	$p < .1$	$\eta_p^2 = .11$
Width	$F_{3,84} = 12.87$	$p < .00001$	$\eta_p^2 = .32$
Amplitude	$F_{2,56} = 95.70$	$p < .00001$	$\eta_p^2 = .77$
Angle	$F_{3.24,90.67} = 30.83$	$p < .00001$	$\eta_p^2 = .52$
Age × Width	$F_{3,84} = 0.76$	$p = .519$	$\eta_p^2 = .03$
Age × Amplitude	$F_{2,56} = 4.43$	$p < .05$	$\eta_p^2 = .14$
Age × Angle	$F_{3.24,90.67} = 6.61$	$p < .0005$	$\eta_p^2 = .19$
Age × Width × Amplitude	$F_{6,168} = 1.16$	$p = .330$	$\eta_p^2 = .04$
Age × Width × Angle	$F_{9.52,266.50} = 1.27$	$p = .251$	$\eta_p^2 = .04$
Age × Amplitude × Angle	$F_{8.21,229.77} = 0.55$	$p = .824$	$\eta_p^2 = .02$
Age × Width × Amplitude × Angle	$F_{42,1176} = 0.71$	$p = .918$	$\eta_p^2 = .03$
Width × Amplitude	$F_{6,168} = 0.17$	$p = .984$	$\eta_p^2 = .01$
Width × Angle	$F_{9.52,266.50} = 0.64$	$p = .769$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{8.21,229.77} = 0.74$	$p = .656$	$\eta_p^2 = .03$
Width × Amplitude × Angle	$F_{42,1176} = 0.83$	$p = .764$	$\eta_p^2 = .03$

Table C.16 Statistical Inference from Mean Yaw (RY)

Factor	**F-Statistics**	**Significance**	**Effect Size**
Age	$F_{1,28} = 0.51$	$p = .481$	$\eta_p^2 = .02$
Width	$F_{2.22,62.21} = 1.24$	$p = .300$	$\eta_p^2 = .04$
Amplitude	$F_{2,56} = 1.06$	$p = .354$	$\eta_p^2 = .04$
Angle	$F_{4.17,116.64} = 4.49$	$p < .005$	$\eta_p^2 = .14$
Age × Width	$F_{2.22,62.21} = 0.04$	$p = .975$	$\eta_p^2 = .001$
Age × Amplitude	$F_{2,56} = 1.38$	$p = .259$	$\eta_p^2 = .05$
Age × Angle	$F_{4.17,116.64} = 1.16$	$p = .333$	$\eta_p^2 = .04$
Age × Width × Amplitude	$F_{6,168} = 0.69$	$p = .661$	$\eta_p^2 = .02$
Age × Width × Angle	$F_{8.91,249.39} = 0.78$	$p = .636$	$\eta_p^2 = .03$
Age × Amplitude × Angle	$F_{5.83,163.28} = 0.66$	$p = .679$	$\eta_p^2 = .02$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.33$	$p < .1$	$\eta_p^2 = .05$
Width × Amplitude	$F_{6,168} = 1.02$	$p = .416$	$\eta_p^2 = .04$
Width × Angle	$F_{8.91,249.39} = 0.52$	$p = .860$	$\eta_p^2 = .02$
Amplitude × Angle	$F_{5.83,163.28} = 1.49$	$p = .188$	$\eta_p^2 = .05$
Width × Amplitude × Angle	$F_{42,1176} = 1.17$	$p = .209$	$\eta_p^2 = .04$

Table C.17 Statistical Inference from Mean Pitch (RP)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 2.24$	$p = .145$	$\eta_p^2 = .07$
Width	$F_{3,84} = 0.55$	$p = .648$	$\eta_p^2 = .02$
Amplitude	$F_{1.42,39.78} = 1.08$	$p = .328$	$\eta_p^2 = .04$
Angle	$F_{4.00,112.07} = 9.88$	$p < .00001$	$\eta_p^2 = .26$
Age × Width	$F_{3,84} = 2.05$	$p = .113$	$\eta_p^2 = .07$
Age × Amplitude	$F_{1.42,39.78} = 0.04$	$p = .917$	$\eta_p^2 = .001$
Age × Angle	$F_{4.00,112.07} = 1.02$	$p = .400$	$\eta_p^2 = .04$
Age × Width × Amplitude	$F_{4.04,113.18} = 0.97$	$p = .429$	$\eta_p^2 = .03$
Age × Width × Angle	$F_{9.48,265.54} = 0.65$	$p = .766$	$\eta_p^2 = .02$
Age × Amplitude × Angle	$F_{6.80,190.27} = 0.80$	$p = .586$	$\eta_p^2 = .03$
Age × Width × Amplitude × Angle	$F_{42,1176} = 0.73$	$p = .898$	$\eta_p^2 = .03$
Width × Amplitude	$F_{4.04,113.18} = 0.51$	$p = .728$	$\eta_p^2 = .02$
Width × Angle	$F_{9.48,265.54} = 0.94$	$p = .497$	$\eta_p^2 = .03$
Amplitude × Angle	$F_{6.80,190.27} = 1.04$	$p = .402$	$\eta_p^2 = .04$
Width × Amplitude × Angle	$F_{42,1176} = 1.14$	$p = .247$	$\eta_p^2 = .04$

Table C.18 Statistical Inference from Mean Roll (RR)

Factor	F-Statistics	Significance	Effect Size
Age	$F_{1,28} = 6.00$	$p < .05$	$\eta_p^2 = .18$
Width	$F_{2.42,67.82} = 0.29$	$p = .790$	$\eta_p^2 = .01$
Amplitude	$F_{2,56} = 0.35$	$p = .709$	$\eta_p^2 = .01$
Angle	$F_{7,196} = 18.32$	$p < .00001$	$\eta_p^2 = .40$
Age × Width	$F_{2.42,67.82} = 0.14$	$p = .902$	$\eta_p^2 = .01$
Age × Amplitude	$F_{2,56} = 0.02$	$p = .980$	$\eta_p^2 = .001$
Age × Angle	$F_{7,196} = 1.23$	$p = .289$	$\eta_p^2 = .04$
Age × Width × Amplitude	$F_{3.73,104.49} = 1.14$	$p = .341$	$\eta_p^2 = .04$
Age × Width × Angle	$F_{9.23,258.41} = 1.09$	$p = .371$	$\eta_p^2 = .04$
Age × Amplitude × Angle	$F_{6.69,187.39} = 1.12$	$p = .353$	$\eta_p^2 = .04$
Age × Width × Amplitude × Angle	$F_{42,1176} = 1.04$	$p = .401$	$\eta_p^2 = .04$
Width × Amplitude	$F_{3.73,104.49} = 2.10$	$p < .1$	$\eta_p^2 = .07$
Width × Angle	$F_{9.23,258.41} = 1.20$	$p = .297$	$\eta_p^2 = .04$
Amplitude × Angle	$F_{6.69,187.39} = 1.53$	$p = .161$	$\eta_p^2 = .05$
Width × Amplitude × Angle	$F_{42,1176} = 0.79$	$p = .827$	$\eta_p^2 = .03$

Appendix D

List of Publications

This appendix contains the list of publications that came out of this thesis.

Refereed Journal Article

[J.1] Sultana, A. & Moffatt, K. (2019). Effects of aging on small target selection with touch input. *ACM Transactions on Accessible Computing (TACCESS), 12*(1), 1. https://doi.org/10.1145/3300178

Workshop Papers

[W.2] Sultana, A., Xu, J. & Moffatt, K. (2018). Towards accessible touchscreen interfaces for older adults: Modeling and visualizing finger trajectories. *Proceedings of the Workshop on Designing Interactions for the Aging Populations, The 36th ACM SIGCHI Conference on Human Factors in Computing Systems (CHI) 2018*, 22–27.

[W.1] Sultana, A., & Moffatt, K. (2017). Target selection difficulties of older adults with small touchscreen devices. *Proceedings of the Workshop on Designing Mobile Interactions for the Aging Populations, The 35th ACM International Conference on Human Factors in Computing Systems (CHI) 2017*, 25–28.

Conference Demo

[D.1] Sultana, A. & Moffatt, K. (2018, October 16–17). *3-D finger trajectory tracking, modelling and visualizing tool for accessible touchscreen interface for older adults* [Conference demo presentation]. AGE-WELL Annual Conference 2018, Vancouver, BC, Canada. https://agewell-nce.ca/wp-content/uploads/2018/12/2018-Abstract-Booklet.pdf.

Conference Posters

[P.4] Sultana, A. & Moffatt, K. (2018, October 18–20). *Understanding finger selection endpoint variability of older adults with handheld touchscreen technologies* [Poster Presentation]. 47^{th} Annual & Educational Meeting of Canadian Association on Gerontology (CAG 2018), Vancouver, BC, Canada.

[P.3] Sultana, A. & Moffatt, K. (2018, October 16–17). *Three-dimensional finger trajectory models to understand touch interaction difficulties of older adults* [Poster Presentation]. AGE-WELL Annual Conference 2018, Vancouver, BC, Canada.

[P.2] Sultana, A. & Moffatt, K. (2017, October 17–19). *Modeling finger trajectories to understand touch interaction of older adults* [Poster Presentation]. AGE-WELL Annual Conference 2017, Winnipeg, MB, Canada.

[P.1] Sultana, A. & Moffatt, K. (2016, October 19–21). *Understanding touchscreen behavior of older adults* [Poster Presentation]. AGE-WELL Annual Conference 2016, Montreal, QC, Canada.

Doctoral Consortium

[DC.1] Sultana, A. (2015). Performance evaluation for touch-based interaction of older adults. *ACM SIGACCESS Accessibility and Computing Newsletter (16th International SIGACCESS Conference on Computers and Accessibility (ASSETS) 2014)*, 111, 38 – 41.

Appendix E

Ethics Approval Certificate

This appendix includes the ethics approval certificate and following amendments from McGill Unveristy Research and Ethics Board to conduct studies for this thesis.

McGill

Research Ethics Board Office
James Administration Bldg. room 429
845 Sherbrooke St West
Montreal, QC H3A 0G4

Tel: (514) 398-6831
Fax: (514) 398-4644
Ethics website:www.mcgill.ca/research/researchers/compliance/human/

Research Ethics Board II
Certificate of Ethical Acceptability of Research Involving Humans

REB File #: 14-0612

Project Title: Advancing Accessible Computing by Considering Real World Use

Principal Investigator: Prof. Karyn Moffatt **Department:** School of Information Studies

Funding Agency/Title: FQRNT / Avancement de l'informatique accessible par la prise en compte de son utilisation en situation réelle

This project was reviewed by delegated review

Annett Koerner, Ph.D.
Delegated Reviewer, REB II

Approval Period: _______________ **to** _______________

This project was reviewed and approved in accordance with the requirements of the McGill University Policy on the Ethical Conduct of Research Involving Human Subjects and with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans.

---

* All research involving human participants requires review on an annual basis. A Request for Renewal form should be submitted 2-3 weeks before the above expiry date.
* When a project has been completed or terminated a Study Closure form must be submitted.
* Should any modification or other unanticipated development occur before the next required review, the REB must be informed and any modification can't be initiated until approval is received.

McGill University

ETHICS REVIEW
AMENDMENT REQUEST FORM

This form can be used to submit any changes/updates to be made to a currently approved research project. Changes must be reviewed and approved by the REB before they can be implemented.

Significant or numerous changes to study methods, participant populations, location of research or the research question or where the amendment will change the overall purpose or objective of the originally approved study will require the submission of a complete new application.

REB File #: **14-0612**
Project Title: Advancing Accessible Computing by Considering Real World Use

Principal Investigator: Prof Karyn Moffatt
Email: karyn.moffatt@mcgill.ca
Faculty Supervisor (for student PI): N/A

1) Explain what these changes are, why they are needed, and if the risks or benefits to participants will change.

We request the following minor changes, none of which change the risks and benefits to the participants:

1. Co-Investigators. Afroza Sultana (afroza.sultana@mail.mcgill.ca), a doctoral student supervised by Prof Moffatt has joined the project and will be leading the data collection. Relevant documentation (consent forms, and calls for participation) have been updated accordingly are included here for review.

2. Location of research. In our original application, we planned to carry out study sessions in a "quiet and private room within the McGill School of Information studies". As travel is inconvenient for many of our participants we wish to revise the setting of our research as follows (italics indicate changes):

> This research will take place in a quiet and private room. *This room may be within the McGill School of Information studies, or in a space more convenient for the participant, such as a quiet room within a local community centre. In either case,* the room will be large enough to comfortably accommodate the researcher and the participant, as well as the equipment necessary to complete the study tasks.

This change should in no way impact the research or findings.

3. Methodology/Procedures. As described in our original application, one of the goals of this research is to identify the sensory and perceptual abilities that influence motor performance of older adults. A series of tests selected from Spreen and Strauss's Compendium of Neuropsychological Tests [1] were included in our protocol to help answer these questions.

Recently work in the area has begun to identify fluid intelligence as an important factor [2, 3]. While Spreen and Strauss's Compendium includes the TONI as a test of fluid intelligence, we wish to instead add the Letter Sets test [4] to our battery, to better facilitate comparison with prior works that have used this test [2, 3]. The Letter Sets test is a brief and easily administered test. Each problem consists of fives sets of four letters. Four of the sets of letters are alike in some way and the goal is to identify the set that doesn't follow the rule. For instance, in the example question below, BDFL is the answer as all the other sets represent series of consecutive letters in the alphabet.

NOPQ $\boxed{\text{DBFL}}$ ABCD HLJK UVWX

In total, the test takes approximately 15 minutes to administer. We will remove other tests from our battery to accommodate this addition and thus the change will have no impact on the overall expected duration for the study.

[1] Spreen, O., & Strauss, E. (1998). A compendium of neuropsychological tests: Administration, norms, & commentary. 2nd ed. New York, NY: Oxford University Press

[2] Trewin, S., Richards, J.T., Hanson, V.L., Sloan, D., John, B.E., Swart, C., and Thomas, J.C. (2012). Understanding the role of age and fluid intelligence in information search. In Proceedings of the 14th international ACM SIGACCESS conference on Computers and accessibility (ASSETS '12). ACM, New York, NY, USA, 119-126. DOI=10.1145/2384916.2384938

[3] Crabb M., and Hanson. V.L. (2014). Age, technology usage, and cognitive characteristics in relation to perceived disorientation and reported website ease of use. In Proceedings of the 16th international ACM SIGACCESS conference on Computers & accessibility (ASSETS '14). ACM, New York, NY, USA, 193-200. DOI=10.1145/2661334.2661356

[4] Ekstrom, R. B., French, J. W., Harman, H. H., & Dermen, D. (1976). Kit of Factor-Referenced Cognitive Tests. Princeton, NJ: Educational Testing Service.

4. Questionnaire. Some of the questions on our questionnaire provide examples of popular software. We have updated one of these to provide more recent examples that will be more familiar to our participants. This change should help clarify the question to participants and ensure they answer it correctly, but does not materially change the survey.

2) Attach relevant additional or revised documents such as questionnaires, consent forms, recruitment ads.

The following documents are attached:
Appendix A: Recruitment Flyers: revised to include contact information for Afroza Sultana
Appendix B: Background Questionnaire: adjusted wording to question 5 of part II
Appendix C: Consent Form: revised to acknowledge Afroza Sultana's role in the research project.

All changes in these documents are highlighted using track changes.

Principal Investigator Signature: ____________ Date: June 15, 2015

Faculty Supervisor Signature: ____________ Date: ____________
(for student PI)

For Administrative Use **REB**: ____REB-I X REB-II ____REB-III

X Delegated Review ____ Full Review

X This amendment request has been approved.

Signature of REB Chair/ delegate: ____________ Date: June 18, 2015

Project Approval Expires: May 31, 2016

McGill University

ETHICS REVIEW
AMENDMENT REQUEST FORM

This form can be used to submit any changes/updates to be made to a currently approved research project. Changes must be reviewed and approved by the REB before they can be implemented.

Significant or numerous changes to study methods, participant populations, location of research or the research question or where the amendment will change the overall purpose or objective of the originally approved study will require the submission of a complete new application.

REB File #: 14-0612
Project Title: Advancing Accessible Computing by Considering Real World Use
Principal Investigator: Prof Karyn Moffatt
Email: karyn.moffatt@mcgill.ca
Faculty Supervisor (for student PI): N/A

1) Explain what these changes are, why they are needed, and if the risks or benefits to participants will change.

After pilot testing our study design with 2 participants, we have identified a number of small changes that need to be made to the questionnaire design. These changes (which are highlighted in the attached appendix) mostly pertain to the use of handheld touch screen devices, a major focus of our study. he changes will help us to distinguish between general computer expertise and experience specific to touch-based interaction. In a few cases, changes were also made to improve the clarity of the text. T

The requested changes do not change the risks or benefits of the study.

2) Attach relevant additional or revised documents such as questionnaires, consent forms, recruitment ads.

The following documents are attached:
Appendix A: Background Questionnaire: adjusted to differentiate participants' experience with computers and handheld devices.

All changes in these documents are highlighted.

Principal Investigator Signature: ______ Date: September 9, 2015

Faculty Supervisor Signature: ______ Date: ______
(for student PI)

For Administrative Use **REB**: ___REB-I X REB-II ___REB-III

✓ Delegated Review ____ Full Review

✓ This amendment request has been approved.

Signature of REB Chair/ delegate: ______ Date: Sept. 17, 2015

Project Approval Expires: May 31, 2016