EFFECTS OF AGE ON SMARTPHONE AND TABLET USABILITY, BASED ON EYE-MOVEMENT TRACKING AND TOUCH-GESTURE INTERACTIONS

BY

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ABSTRACT

The aim of this thesis is to provide an insight into the effects of user age on interactions with smartphones and tablets applications. The study considered two interaction methods to investigate the effects of user age on the usability of smartphones and tablets of different sizes: 1) eye-movements/browsing and 2) touch-gesture interactions. In eye movement studies, an eye tracker was used to trace and record users' eye movements which were later analysed to understand the effects of age and screen-size on browsing effectiveness. Whilst in gesture interactions, an application developed for smartphones traced and recorded users' touch-gestures data, which were later analysed to investigate the effects of age and screen-size on touch-gesture performance. The motivation to conduct our studies is summarised as follows: 1) increasing number of elderly people in our society, 2) widespread use of smartphone technology across the world, 3) understanding difficulties for elderly when interacting smartphones technology, and 4) provide the existing body of literature with new understanding on the effects of ageing on smartphone usability.

The work of this thesis includes five research projects conducted in two stages. *Stage One* included two researches used eye movement analysis to investigate the effects of user age and the influence of screen size on browsing smartphone interfaces. The first research examined the scan-paths dissimilarity of browsing smartphones applications for elderly users (60+) and younger users (20-39). The results revealed that the scan-paths dissimilarity in browsing smartphone applications was higher for elderly users (i.e., age-driven) than the younger users. The results also revealed that browsing smartphone applications were stimulus-driven rather than screen size-driven. The second study was conducted to understand the difficulties of information processing when browsing smartphone applications for elderly (60+), middle-age (40-59) and younger (20-39) users. The evaluation was performed using three different screen sizes of smartphone and tablet devices. The results revealed that processing of both local and global information on a smartphone/tablet interfaces was more difficult for elderly users than it was for the other age groups. Across all age groups, browsing on the smaller smartphone size proved to be more difficult compared to the larger screen sizes.

Stage Two included three researches to investigate: the difficulties in interacting with gesture-based applications for elderly compared to younger users; and to evaluate the possibility of classifying user's age-group based on on-screen gestures. The first research investigated the effects of user age and screen size on performing gesture swiping intuitively for four swiping directions: down, left, right, and up. The results revealed that the performance of gesture swiping was influenced by user age, screen size, as well as by the swiping orientation. The purpose of the second research was to investigate the effects of user age, screen sizes, and gesture complexity in performing accurate gestures on smartphones and tablets using gesture-based features. The results revealed that the elderly were less accurate, less efficient, slower, and exerted more pressure on the touch-screen when performing gestures than the younger users. On a small smartphone, all users were less accurate in gesture performance – more so for elderly – compared to mini-sized tablets. Also, the users, especially the elderly, were less efficient and less accurate when performing complex gestures on the small smartphone compared to the mini-tablet. The third research investigated the possibility of classifying a user's age-group using touch gesture-based features (i.e., gesture speed, gesture accuracy, movement time, and finger pressure) on smartphones. In the third research, we provide evidence for the possibility of classifying a user's age-group using gesture-based applications on smartphones for user-dependent and user-independent scenarios. The accuracy of age-group classification on smaller screens was higher than that on devices with larger screens due to larger screens being much easier to use for all users across both age groups. In addition, it was found that the age-group classification accuracy was higher for younger users than elderly users. This was due to the fact that some elderly users performed the gestures in the same way as the younger users do, which could be due to their longer experience in using smartphones than the typical elderly user.

Overall, our results provided evidence that elderly users encounter difficulties when interacting with smartphones and tablet devices compared to younger users. Also, it was possible to classify user's age-group based on users' ability to perform touch-gestures on smartphones and tablets. The designers of smartphone interfaces should remove barriers that make browsing and processing local and global information on smartphones' applications difficult. Furthermore, larger screen sizes should be considered for elderly users. Also, smartphones could include automatically customisable user interfaces to suite elderly users' abilities to accommodate their needs so that they can be equally efficient as younger users.

The outcomes of this research could enhance the design of smartphones and tablets as well the applications that run on such devices, especially those that are aimed at elderly users. Such devices and applications could play an effective role in enhancing elderly peoples' activities of daily lives.

TO MY FAMILY

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There are a number of people without whom this thesis might not have been written, and to whom I am greatly indebted. I would like to dedicate the outcome of this work to my father, who has been waiting for so long to see his son's work has been done successfully, to my mother who has been a source of encouragement and inspiration to me throughout my life, a very special thank you for praying all the time for this work to be done. Also, my thankfulness and appreciation to my extended family, my brothers and sisters for their support, encouragement, patience and praying for me, particularly judge Abdullah, without his supporting and encouraging I would not take the opportunity to start with the course of PhD.

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Declaration

*I hereby declare that all the work in my thesis entitled "**Effects of Age on Smartphone and Tablet Usability, based on Eye-Movement Tracking and Touch-Gesture Interactions**" is my own work except where due reference is made within the text of the thesis.*

I also declare that, to the best of my knowledge, none of the material has ever previously been submitted for a degree in the University of Buckingham or any other university.

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LIST OF ABBREVIATIONS

ANOVA	analysis of variance (statistical procedure)
DTW	dynamic time warping
ED	Euclidean distance
EXP1	experiment 1
EXP2	experiment 2
GUI	graphical user interface
FD	fixation duration
FP	finger pressure
HCI	human-computer interaction
ID	Inclusive Design
MT	movement time
N	sample size (statistical parameter)
n^2	Eta-square (measure the strength of the effect of different variables)
P	probability (statistical parameter)
RSTFP	ratio of speed to finger pressure
SA	saccades amplitude
RS	Ratio of saccades
SPD	scan-path duration
STD	standard deviation (statistical parameter)
UI	User Interface

CHAPTER 1

INTRODUCTION

Smartphone technologies have been evolving at a rapid pace in various aspects such as screen-size and resolution, interface designs, network communications abilities, and applications. This has enabled users to use their smartphones in a variety of activities of daily life. Social networking, m-commerce, education, web browsing, healthcare, entertainment, instant messaging and video conferencing, and task management are some but few popular applications on smartphones. It is worth noting that the Apple iPhone – the first smartphone as we know them today – was released in 2007, just eight years ago. Smartphones and their applications are now an integral part of our lives and the ways in which we interact with others whether socially or in business.

Whilst technology e.g. smartphones can, and they do, play an important role in our daily lives, evidence suggests that users who were not exposed to the technology during their 'formative years' find the interaction with technology difficult (e.g. (Stößel, 2012)). This difficulty is exacerbated for elderly (60+ years old) because of their age-related deficits in sensation and perception, motor movement and cognitive abilities (Chen, 2013). Due to lack of experience in the use of technology e.g. PCs and smartphones, as well as their applications in general and age-related physiological and psychological issues in particular, elderly are faced with many obstacles in adopting rapidly evolving smartphone technologies, which otherwise could assist them in their activities of daily life (Evans & Minocha, 2013). There is also the problem of device manufacturers and application developers focusing their efforts in tailoring the design of smartphones and applications to younger generations and those in work in order to target a larger share of the market (Stößel, 2012).

Considering elderly users' abilities, limitations and their needs when designing technological solutions could allow elderly live independently. Such solutions could provide elderly people convenient and timely access to the benefits of using healthcare systems, important and relevant information, or to communicate with family, friends and carers that will help them overcome isolation (Minocha, et al., 2013), (Farage, et al., 2012).

Previous studies have shown that there is a digital divide between elderly users and younger users (e.g. Stößel, 2012)). It was recommended by (Chen, 2013) to conduct studies to understand the difficulty level for elderly when interacting with touchscreen technology.

Based on previous recommendations and the limited number of studies on smartphone usability in the literature, there is a need for further systematic investigation on smartphones' usability for the elderly users. Previous recommendations were for visual search studies using eye movement (Fukuda, 2008), (Obrist, et al., 2007), and gestures using finger touchscreens in the context of smartphone applications (Chen, 2013), (Stößel, 2012). Such studies should consider ageing with the accompanied changes in sensation and perception, motor movement, and cognitive abilities impairments (Chen, 2013). To the best of our knowledge, there was no study conducted for elderly users to evaluate the usability of small smartphones and tablets based on eye movement and touch-gesture interactions. Our study has endeavoured to focus on smartphones and tablets devices for elderly using touch-gestures.

The rest of this chapter is organised as follows: issues that motivated this research are presented in Section 1.1; the key research questions pursued in this thesis are discussed in Section 1.2; Section 1.3 explains the main aims and the focus of the study; Section 1.4 provides a brief overview of the thesis organisation which is followed by Section 1.5 where our publications to-date are listed.

1.1. Motivation

The motivation to conduct an investigation into how the elderly interact with smartphone technology was driven by three main factors. First motivation is the significant increase of the elderly population. Based on the (AgeUK, 2015) report for people who are living in the UK, people aged 60+ years old number more than those aged 18 years old and below. Also, the elderly population aged over 60 in the UK is now nearly 14.5 million. The percentage of people currently living in the UK aged 60 to 64 years old is almost 55% of the total elderly population. Globally, the elderly persons aged 60+ are growing faster than the total population (Deloitte, 2014).

Across the world, the number of persons aged 60+ years is approximately 810 million in 2012 and by 2050 this number is predicted to grow to more than 2 billion. At that point, elderly people will outnumber the population of those aged 0-14 years for the first time in human history. Asia has more than half (55%) of the world's elderly persons, followed by Europe, which accounts for 21% of the total (Nations, 2012).

Our second motivation is the widespread use of smartphone technology across the world and its potential benefits to elderly people. For example, based on the ICT report (ICT, 2013) that the mobile-cellular subscriptions in Europe were estimated to be around 126 per 100 people. Also, the highest internet usage is in the Europe region (i.e., 75%), followed by the Americas (i.e., 61%). According to recent figures showed by (Consulting, 2013) that has been conducted for all online shoppers, 39% of 60+ years old now own a smartphone device and 21 percent of 70-79 years old own a tablet device (Consulting, 2013). However, the average use of smartphone devices and applications by the elderly is still low (Deloitte, 2014), despite the obvious benefits such technology can bring to elderly users. The third motivation is to understand the usability issues faced by elderly people when using smartphone applications in order to make it easier for them to use smartphone applications. This is due to limited number of studies on the effects of ageing on the usability of smartphones, especially using eye-movement tracking and touch-gesture interactions (Chen, 2013), (Stößel, 2012), (Fukuda & Bubb, 2003). The fourth motivation is to provide the existing body of literature with new understanding on the effects of ageing on smartphone usability.

In order to increase the usability of smartphones and tablets, and to provide an empirical and a theoretical study to existing body of literature using eye movement and touch-gesture interactions on smartphones for the elderly, we derived a set of hypotheses based on the background experience of technology use e.g. PCs and smartphones for the elderly. This basis included the difficulty that the elderly encounter when interacting with technology in general, and a literature review of studies conducted on the two interaction methods and elderly users (more details of the hypotheses are given in Section 4.4).

In human-computer interaction, the input methods affect the usability of an interactive system and make the interaction effective (or not). Eye movement analysis is increasingly being used in HCI to provide empirical evidence in evaluation studies because of its high gaze accuracy (Andrienko, et al., 2012). Moreover, eye movement is being used as an input mechanism on modern smartphones (for example to adjust screen brightness depending on whether the user is looking at the screen or not). According to Tibken and Dolcourt (Tibken & Dolcourt, 2013), navigation on a phone can be performed with user's eye. Gestural interactions are ushering in a new era of the technology design because of its intuitive use on touchscreens (Chen, 2013), (Stößel, 2012). Intuitive means natural to use gestures on touchscreens and learning ability without prior training, as well as quick to interact with touchscreens devices (Chen, 2013). In our thesis, we will use eye-movement and touch-gestures as interaction methods to investigate the effects of ageing on smartphone usability.

1.2. Research Questions

Due to the increased population of elderly people in the world, and the widespread use of smartphone technologies, it is extremely important to understand the effects of age on the usability of rapidly evolving smartphone technology. Studies in HCI are required to minimise the "digital divide" between elderly users, and younger users.

In this thesis, we pose the following research questions on the effects of age on smartphones and tablets applications:

> **Q1**: What is the effect of age in browsing smartphone applications using eye movements? (H1 – H4)
>
> **Q2**: To what extent could elderly perform gesture swiping on smartphone interfaces without needing to training? (H5 & H6)
>
> **Q3**: What is the effect of age on executing accurate gestures on smartphones using gesture-based applications? (H7 – H14)
>
> **Q4**: Could we use gestures performed on smartphone applications to classify user age? (H15 & H16)

1.3. The Aim and Focus

The aim of this thesis is to gain an insight into the effect of user age on interactions with smartphone and tablet applications using eye movement and touch-gesture interactions. Based on the attained insight, it is hoped the hardware and software designers could lower, if not remove all together, some of the barriers faced by elderly in using applications on smartphones and tablets. The overall objectives of this thesis are:

1. Investigate the effects of user-age and screen-size on smartphones' and tablets' usability using eye movement tracking.
2. Investigate the effects of user-age and screen-size on smartphones' and tablets' usability using touch-gesture interactions.
3. Assess the possibility of classifying user's age-group using gesture-based features on smartphones and tablets.
4. Propose methods and guidelines to enhance the usability of smartphones and tablets for elderly users.

Five studies, organised in two stages as shown in Figure 1 below will be used to achieve the objectives of the thesis. *Stage One* includes two researches to investigate the effect of user-age and influence of screen-size on browsing smartphone interfaces using eye movement. The first research will examine the scan-path dissimilarity of browsing smartphones applications for elderly users (60+) and younger users (20-39). The aim of second research is to understand the difficulties of information processing when interacting with smartphone applications for elderly (60+), middle-age (40-59) and younger (20-39) users. The evaluation will be performed using three different screen sizes of smartphone and tablet devices.

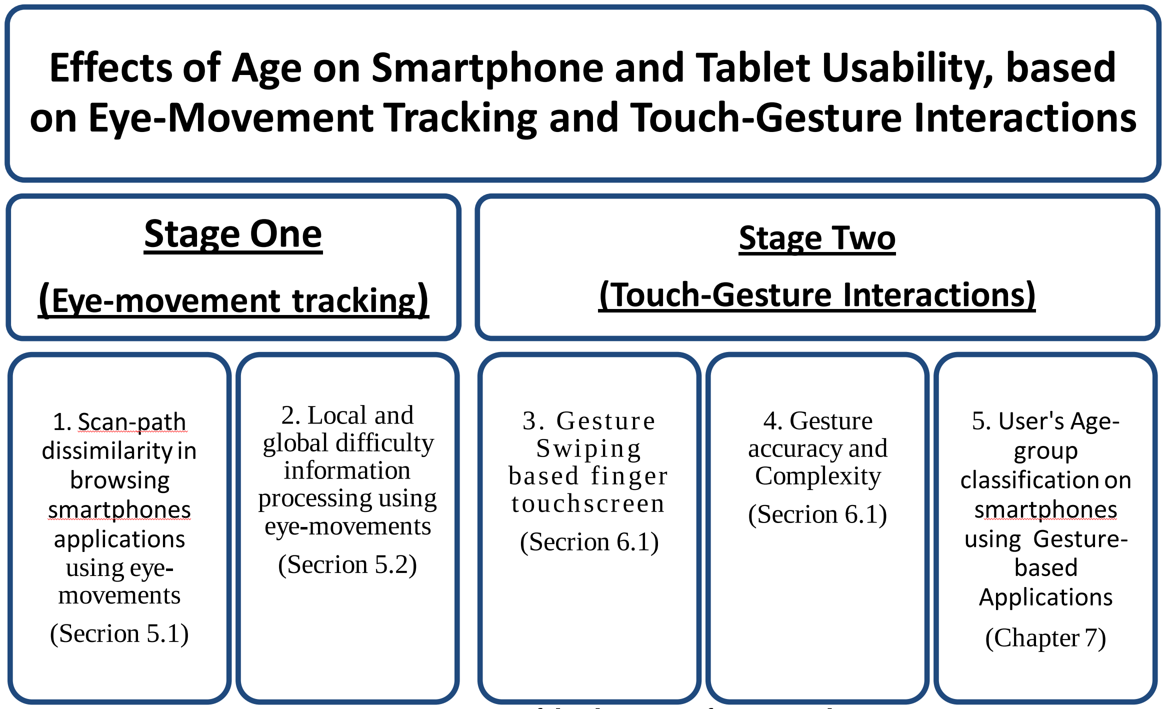


Figure 1. Organisation of the thesis into five research projects.

Stage two includes three researches that investigate the difficulties in interacting with gesture-based features for elderly compared to younger users, and to evaluate the possibility of classifying user's age-group based on on-screen gestures. The first research investigated the effect of user-age and screen-size in performing gesture swiping intuitively for four swiping orientations; down, left, right, and up. The purpose of second research is to investigate the effect of user age, screen sizes, and gesture complexity in performing accurate gestures using gesture-based features on smartphones and tablets. The third research investigates the possibility of classifying user's age-group using gesture-based features on smartphones. In the third research, we aim to provide evidence for the possibility of classifying user's age-group using a gesture-based application on smartphones for user-dependent and user-independent scenarios. Also, we suggest to use the user's age-group classification study as a system to let the users interact with the smartphones technology based on their abilities that will let the system turn into a particular setting to fit their ability, especially for elderly users. This will lead to customized user interfaces that will increase the usability of smartphones and tablets for elderly users.

1.4. Thesis Overview

The rest of the thesis is organised as follows:

Chapter 2 presents significant physiological and psychological changes related to ageing and an overview of elderly people's attitudes, anxiety and expectations towards technology use e.g. PCs and smartphones. By reviewing number of previous studies, this chapter provides further evidence of pointing difficulties (e.g. mouse, pen-based), difficulties with smaller screen sizes and technologies designed for elderly users. In addition, the problems of technology designs that strive to accommodate elderly needs will be presented.

Chapter 3 reviews existing literature on elderly users' experience with technology use e.g. PCs and smartphones in general, and a review of usability studies based on the two interaction methods, namely eye movement and gesture interactions, for elderly users.

Chapter 4 presents a definition of age groups of people who will be involved in the thesis. A description of all smartphone devices, study metrics and hypotheses that will be evaluated in this study will be given in this chapter.

Chapter 5 presents two researches conducted on interface browsing for elderly users using eye movement on smartphone applications.

Chapter 6 presents two researches conducted on gesture-based features using smartphones and tablets for elderly users; gesture swiping interactions, and gesture accuracy and complexity.

Chapter 7 presents a research that investigated the user age-group classification using gesture-based features on smartphones. The influence of screen sizes on users of different age groups was examined.

Chapter 8 presents an overview and summary discussion on the results from the two stages of this thesis. Subsequently, details for the study motivation, the general limitations, and study challenges will be given. Finally, our contributions, implications, and future work will be discussed.

1.5. Publications

The following papers were presented and published during the course of this research.

1. S. Al-Showarah, N. Al-Jawad, H.Sellahewa, (2013). "*Examining eye-tracker Scan-paths for elderly people using smart phones*". York Computer Science (YCS) technical report - University of York, 29th October, pp. 255-261.
2. Al-Showarah, S., AL-Jawad, N. & Sellahewa, H., 2014. *"Effects of User Age on Smartphone and Tablet Use, Measured with an Eye-Tracker via Fixation Duration, Scan-Path Duration, and ratio of Saccades*". Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8514 LNCS (PART 2), pp. 3-14.
3. S. Al-Showarah, N. Al-Jawad, H.Sellahewa, (2014). "*User's Age Classification on Smartphones using Gesture-based Applications*". BCS London Doctoral Consortium 2014, 22 May 2014, London Central Branch.

CHAPTER 2

ELDERLY USERS AND TECHNOLOGY

Ageing is generally accompanied by a variety of changes that are represented by impairments in sensation and perception, cognitive ability, and motor movement ability. Designers of interfaces technology e.g. PCs and smartphones must understand age-related physiological, psychological characteristics and social aspects that have an impact on user's performance when using technology (Chen, 2013), (Victor, 2010), (Fisk, et al., 2009). This chapter presents an overview of relevant age-related impairments and a discussion on how they affect the typical elderly user's performance, and the obstacles that the elderly users may face when interacting with technology. Furthermore, the chapter presents an overview of how the attitudes of elderly people, their anxiety and inexperience affect their use of technology. Readers familiar with aforementioned age related impairments may skip section 2.1.

By reviewing a number of studies, this chapter provides further evidence of the actual problems with pointing difficulties (e.g. mouse, pen-based), difficulties with smaller screen sizes, and technology designs faced by elderly users. Furthermore, this chapter outlines the problems with different kinds of designs that strive to accommodate elderly needs.

2.1. Physiological and Psychological Characteristics of Ageing

This section provides a brief explanation of the key physiological and psychological characteristics that changes with ageing and how these changes affect human interactions with technology.

Figure 2 shows the model human information processing by (Card, et al., 1983). According to the model human information processing we receive information via input channels (e.g. vision) when interacting with technology, e.g. PCs or smartphones. The information will be processed in the brain and saved in the memory (sensory memory, short-term memory, and long-term memory), and then the response will be given via output channels (motor control behaviours) (Downton, 1991).

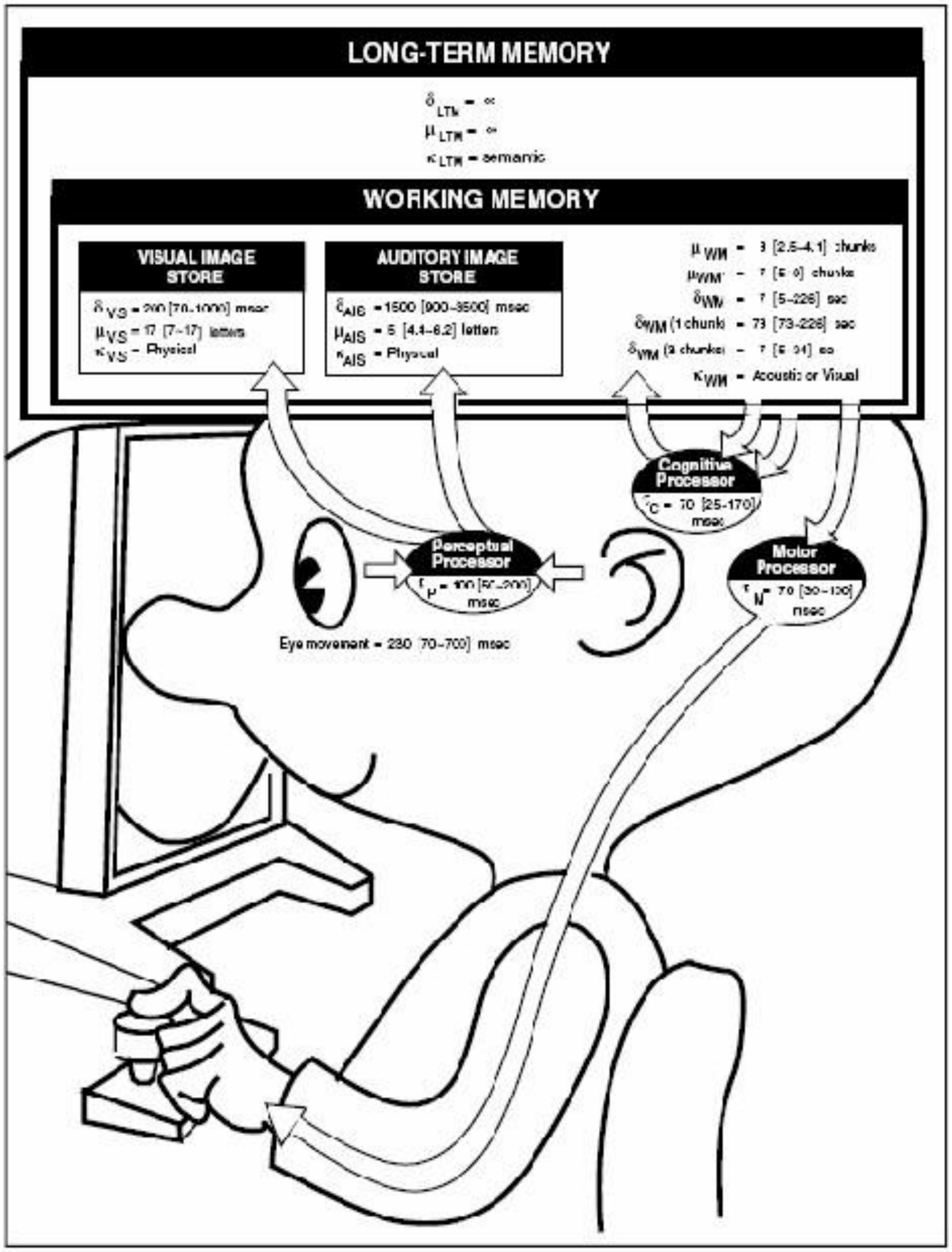


Figure 2. Model Human Information Processing for HCI (source: (Downton, 1991)).

2.1.1 **Sensation and Perception**

The sensory perception of touch is one of the human physiological changes affected by ageing. This section discusses, two human senses modalities due to their link to the two interaction methods used in the thesis; vision that is used for eye movement and finger-based touchscreen that is used for touch-gesture interactions.

Vision

Vision is the most important input source of information for humans. It was stated by (DIX, et al., 2004) that the visual perception of humans can be divided into two stages. First, the human eye receives the stimulus (information) by the visual apparatus (sight) from the outside world. Secondly, the information is then transferred to the human brain for processing, to allow us to recognise and to distinguish that stimulus (e.g. colour). The human brain is involved more in visual processing than with any other sense (e.g. touch, smell, etc.) (Gonzalez, 2012). DIX et al. (DIX, et al., 2004) stated that human eye has a very important role in recognising interface contents, where colour is a good example to be recognized by the eye based on information processing using the human brain. It was reported by (Yarbzls, 1967) that human beings can perceive 80% of information that fixated voluntarily and involuntarily on the interface contents through users' eyes. This information may give important indications and useful information regarding the user's familiarity with the perception of objects that can be used to improve the usability of technology for users.

Touch

Touch is also an important human sense. It was stated by (DIX, et al., 2004) that tactile perception provides us with very crucial information about our environment; it provides us with feedback when our hands make contact regarding shape, size, or where our fingers are located. It was concluded by (e.g. (Stößel, 2012), (DIX, et al., 2004)) touch perception informs us if an action has been successfully performed (e.g. a button pressed), this is the meaning of perception. Touch sense based on human fingers is an important source in feedback used in interactions, as also used to control technology (Chen, 2013), (Linghao & Ying, 2010), (Piper, et al., 2010), (Bhuiyan & Picking, 2009). The successful interactions depend on the user's ability to interact with technologies which is achieved through use one of input methods (e.g. keyboard, mouse, touchscreen, or voice) (Rogers, et al., 2005). More details on elderly deficits for sensory perception of touch when interactions with technology are given in Section 2.2.1.

2.1.2 **Cognitive Abilities**

Cognitive abilities are defined as a set of mental processes that comprise memory, visual attention, learning, reasoning, problem solving, producing and understanding language, and decision making (Neisser, 1967). A declining cognitive ability is considered as one of the changes in ageing that makes interaction with technology difficult when information processing (Granata, et al., 2010), (Duval, et al., 2008). The human perceptions depend on the cognitive ability, where the cognitive ability links between human sensory and human reactions. Humans will react (i.e., process information) based on their cognitive ability for what is received through the senses, where the cognitive effort needed to perform a successful task is vary among persons (DIX, et al., 2004), (Mesulam, 1998). This section reviews the cognitive ability issues related to ageing.

Memory

The human information repository is the human memory. Memory has three functionality types: sensory-memory, short-term and long-term memories. The sensory-memory acts as buffers for the information that is received through the human senses. The information will pass into short-term memory that acts as a 'scratch-pad' for temporary recall by attention, so the human can use the information again. The information will be filtered for relevance at a given time, and then will be passed into a more permanent memory store (DIX, et al., 2004). The ability of working memory is influenced particularly by age (Fisk, et al., 2009). Many daily activities can be negatively influenced by decline in human working memory such as problem solving and language comprehension (Granata, et al., 2010). It was suggested by (Dhillon, et al., 2011) (Arnott, et al., 2004), that technology interface designs should be provided by all the required information relevant to that particular task in order to avoid information load from steps; this is to compensate the user’s memory decline.

The long term memory is a store for factual information, all information coming from experience, and also behaviour rules (DIX, et al., 2004). Retrieving information from long-term memory for elderly people is difficult, where this memory is commonly not lost completely (Fisk, et al., 2009). There are three different kinds of long-term memory. The first of which is semantic memory, which remains intact and largely unchanged by age, and is the repository of world knowledge with the ability to remember factual information such as the meaning of words (Fisk, et al., 2009). The second is prospective memory, which refers to the ability to remember to do something in the future. The prospective memory can be split into two parts: 1) Event-based prospective memory that refers to remembering to do something after a specific event has occurred (e.g. turn off the oven after cooking) and 2) Time-based prospective memory that is triggered by time. It is more difficult for an older person that to remember to perform a task after a specific lapse of time (e.g. take medicine in each 6 hours) (Fisk, et al., 2009). The third type of long-term memory is procedural memory, which refers to how to perform tasks learned in the past (Zimmermann, 2014). This memory is concerned with the knowledge that was learned in the past such as how to do automatic actions (e.g. driving a car) or a well-practiced routine (e.g. cooking a food), which remains fairly unchanged.

Recent work on elderly cognitive ability (e.g. (Zimmermann, 2014), (Fisk, et al., 2009)) has shown that older persons behaviours may become slower if their performance requires more attention, and it will be difficult to remember automatic procedures if they are altered by a new context and behaviours. Fisk et al. (Fisk, et al., 2009) stated that developing automatic processes and learning new procedural tasks is more difficult for elderly people.

Attention

Attention is the capacity to keep a user focused on a specific stimulus. This ability changes with increasing age (Farage, et al., 2012). Attention refers to the user’s limited capacity of visual search and mental ability when information processing (Fisk, et al., 2009).

There are three kinds of mechanisms that should be considered in order to understand the term attention, each responsible for a specific part where information will be processed (Stößel, 2012), (Cavanaugh & Blanchard-Fields, 2005). The first of which is selective attention that refers to the ability to choose relevant information to process. Additionally, selective attention is mainly linked to the visual search mechanism as it is required to interact with visual interfaces to identify a target among others (Quigley, et al., 2010), (Fisk, et al., 2009). Several studies reported (e.g. (Quigley, et al., 2010)) that elderly have difficulty in selective attention; this is because of their impairment in visual processing, which causes a failure in perception for the user rather than response to the selection. The second is divided attention (i.e., attentional capacity), it is the ability to simultaneously focus attention on more than one task in a given time (Seçer & Satyen, 2013), (Fisk, et al., 2009). Previous studies reported (e.g. (Seçer & Satyen, 2013)) that divided attention declines with increasing age, where the elderly have less attentional ability to perform dual tasks, this will make the performance less for one task or all tasks. The third type of information processing mechanisms is sustained attention which is the ability to sustain focus and spend a long period of time on a specific task. Quigley et al. (Quigley, et al., 2010) stated that the sustained attention could be a good example for elderly users that they have difficulty to ignore irrelevant information that takes a longer time to perform a task and they also become distracted more easily by details.

In summary, ageing often results in a decline in memory and attention abilities. The impairments in elderly users' abilities make information processing and performing tasks difficult (Granata, et al., 2010), (Fisk, et al., 2009), (Duval, et al., 2008).

2.1.3 Motor Movement

Motor movement is considered as one of the most notable physical characteristics that changes with ageing (Arnott, et al., 2004). It was stated by (Chen, 2013), (Piper, et al., 2010), and (Findlater, et al., 2013) that deficits in motor movement abilities of elderly people almost results in slower performance of a task. The reaction time and accurate performance varies according to ability. For example, as it was reported by (DIX, et al., 2004), the human brain receives number of processing stages to perform a task (e.g. hit a button) through sensory receptors. Based on what is received, the brain will tell the appropriate muscles to respond to perform that task. Each of these processing stages will take time and can be divided into two parts; reaction time and movement time. Movement time depends, to a significant extent, on the physical characteristics of users (e.g. age, fitness). Therefore, motor movement ability is an important part in the timely and accurate performance of a task.

2.2. Elderly People and Interaction Difficulty with Technology

There are at least three main factors that hinder elderly users when they interact with technology. These are: 1) ageing related impairments on physiological and psychological characteristics (these were discussed earlier in Section 2.1), 2) inexperience in technology use, 3) complex technology interface designs (we will discuss different kinds of technology designs in Section 2.2.3).

This section provides further evidence of problems faced by elderly by reviewing a number of studies on pointing difficulties, technology design and screen sizes. It also presents a discussion on elderly users' attitude, and their anxiety towards technology use. Several kinds of technology designs mentioned in the literature that strive to accommodate elderly abilities will also be discussed.

In terms of the elderly experience in technology use, it was reported by (Arnott, et al., 2004) that elderly have much less experience in technology use than younger users. In addition, it was concluded by (e.g. (Guillaume & Nadine, 2010)) that learning how to use a technology such as a computer for elderly users is difficult, and they are more likely to make many mistakes when performing tasks. Recent studies highlighted that elderly people are not being exposed to and did not use such systems during their 'formative years', and their physiological and psychological impairments as reasons for the difficulties they face when using technology (e.g. (Chen, 2013), (Stößel, 2012)). These reasons can play a role in hindering elderly people's interactions with technology, and make technology acceptance very low among them, which then will affect their attitude towards technology.

2.2.1 Influence of Ageing Impairements on Performance

A number of studies (e.g. (Piper, et al., 2010), (Arnott, et al., 2004)) stated that both human manual touch dexterity and vision sensitivity play an important role when interacting with technology devices that require accurate motor movements in order to be operated. For example, Phiriyapokanon (Phiriyapokanon, 2011) reported that impairment in motor control of elderly users makes the interaction with a PC using a mouse difficult.

Piper et al. (Piper, et al., 2010) concluded that the *physical limitations* of ageing have a negative effect on performing a task, especially on small touchscreen sizes. Several studies (e.g. (Findlater, et al., 2013), (Chen, 2013), (Iwase & Murata, 2002),) in the field of physical limitations have found out that the elderly require longer time for mouse pointing targets on interfaces than younger and middle-aged users, where the error rate increases when the distance to the target increases, and the target decreases in size. It was stated by

(Guillaume & Nadine, 2010) that touchscreen could be difficult for elderly when items on the visual screens are crowded.

It was reported by (Chen, 2013) that there have been a limited number of researches regarding the usability of gesture-based applications for elderly users. For example the study by (Stößel, 2012) was conducted on large touchscreen device (i.e., stationary touchscreen). In this context, we decided to conduct further investigations on the usability of smartphones/tablets based on finger-based touch-interaction using gesture-based features for elderly users.

A number of previous studies such as (Phiriyapokanon, 2011), (Kim, et al., 2007), and (Arnott, et al., 2004) found that reduced *vision capability* for humans is the most common reason for problems when interacting with technology and worse when interacting with small items on visual display (e.g. font size), which slows down the speed of performing a task. It was reported by (Arnott, et al., 2004), (Harwood, 2001) that visual acuity worsens after the age of about 50, where many elderly people encounter visual difficulties that will have a larger influence on their ability to use computer technology effectively; the user's ability to browse a visual display in searching for a specific target will be degraded by the difficulty in recognising and distinguishing small items, as well as by complex interface design, and their lack of experience in using technology.

Several studies (e.g. (Linghao & Ying, 2010), (Piper, et al., 2010)) have considered the reduced visual acuity of elderly people by proposing guidelines for technology design like enlarging visual information on a touchscreen surface. Some studies (e.g. (Phiriyapokanon, 2011), (Kim, et al., 2007), (Arnott, et al., 2004)) reported that visual search behaviour can be negatively influenced by the impairment of visual function and cognitive ability (e.g. memory). Based on using eye movement on PC, Fukuda and Bubb (Fukuda & Bubb, 2003) concluded that elderly users are less efficient than younger users when using visual browsing on web pages, and elderly require a longer time than younger users to perform a given task. Further investigation on eye movement based studies are recommended by (Fukuda, 2008), (Fukuda & Bubb, 2003) due to limited studies in this area.

Kobayashi et al. (Kobayashi, et al., 2011) conducted study using a small screen (i.e., iPod 3.5') and large touch screen (i.e., iPad 9.7') to understand elderly users' difficulty on small screen sizes. Their results revealed that the performance on the large screen size out-performed the small screen size for dragging, pinching and tapping, and elderly users found touchscreens were generally easy to use. Screen sizes have an influence on performance, where some of studies (e.g. (Stößel, 2012)) concluded that increasing screen sizes increases the efficiency for the elderly in performing tasks. Nicolau and Jorge (Nicolau & Jorge, 2012) stated that the error rate based on text-entry for elderly users compared to younger users was larger by 26% on a small mobile phone (3.5”) compared to 17% with an ASUS Transformer TF101 Tablet (10.1”). In line with previous studies, we expect that increasing screen size will have a positive influence on elderly performance when browsing smartphones applications using eye movement (hypothesis H4).

In our thesis, we are interested in two interaction methods on smartphones and tablets: finger-based gestures on touchscreens and eye movement. Use of touch-gesture based interactions on smartphones is considered a recent development and a growing technology that provides a natural, direct and an intuitive way of interaction with a technology, allowing easier interaction for the elderly group of people (e.g. (Loureiro & Rodrigues, 2011)). Eye movement is being used increasingly in HCI to provide empirical evidence because of its high gaze accuracy (Andrienko, et al., 2012), (Miyoshi & Murata, 2001).

In summary, elderly users have difficulty with technology use, where this difficulty might be increased by deficits in ability of users and less experience technology use, by complex interface designs, and by small interface items, as well as small screen sizes. Moreover, several studies advocate preferential interface design for the elderly and recommended conducting further studies on both eye movement and gestures for the limited number of studies on these two interaction methods for elderly.

2.2.2 **Elderly Attitude and Anxiety towards Technology Use**

Attitude and anxiety are two different words used to measure how technology is accepted by users. Attitude is a psychological concept which refers to the feelings and user’s behaviour towards something (e.g. technology use). Anxiety is a clinical term, which refers to stressful emotional feelings when thinking about using something (Kelley & Charness, 1995). Moreover, the concept of anxiety is used as a measure for the user’s attitude to using a computer (Gardner, et al., 1993).

The challenges for elderly users of technology use as stated by (e.g. (Kelley & Charness, 1995), (Gardner, et al., 1993)) started with issues related to elderly physical impairments and psychological difficulties. For instance, Bikson and Bikson (Bikson & Bikson, 2001) stated that users who are less trained and are less familiar with technology use are often anxious about causing mistakes and damage to technology system, where it was reported by (Chen, 2013) that elderly users have fearing to cause a damage to the system. Several studies (e.g. (Chen, 2013)) reported that elderly users feel afraid, uncomfortable when using technology and they feel that they cannot be confident in their own capabilities.

The anxiety and low confidence of the elderly can establish severe barriers to using technology. However, other studies (e.g. (Chen, 2013), (Stößel, 2012), (Leitão, 2012), (Tu, 2012), (Arning, et al., 2010)) have concluded that elderly users' general attitude towards technology and their performance can be improved when they understand the benefits of adopting a technology, by technology designed more intuitively to better match their needs, ability, and to their expectations, and when they are trained on computer-based skills. A number of studies (e.g. (Stößel, et al., 2009), (Leitão, 2012)) stated that elderly users are physically able to perform better on the task when properly trained. However, it was concluded by (Farage, et al., 2012) that elderly users need slow steps and frequent repetition of training for technology use.

Chen (Chen, 2013) stated that elderly users often experience social isolation. While several studies (e.g. (Evans & Minocha, 2013), (Caprani, et al., 2012)) reported that adopting and enabling elderly people to participate in technology can assist to minimize the feeling of isolation that many elderly users experience, and this will provide them with access to technology and contact with their friends and family. Hence, Evans and Minocha (Evans & Minocha, 2013) suggested that using social media applications can enhance and improve quality of life for elderly people.

A number of studies (e.g. (Chen, 2013), (Caprani, et al., 2012)) recommended to conducted further investigation on elderly users' difficulty, their vulnerability and their general attitude towards technology use, this is to understand elderly difficulty level that will help to guide better technology design with more usability and make technology tailored to accommodate elderly ability. For example, Minocha et al. (Minocha, et al., 2013) conducted a study on social media (e.g. Facebook, Flicker, Twitter, and YouTube) to investigate the role of technology on the quality of life for users aged over 65. Their investigation aimed to enhance and maintain social connectedness, overcoming social isolation and building supportive relationships and companionship amongst the elderly. They reported that not all older people are vulnerable or socially isolated and in need of help, some of the older people are in fact active and can use technology as younger users do.

A number of previous studies (e.g. (Wagner, et al., 2010), (Su & Li, 2010), (Verstockt, et al., 2009)) stated that elderly users use mobile-phones in a very different way from younger users as regards operating commands and frequency use. Whilst several studies (e.g. (Evans & Minocha, 2013), (Chen, 2013)) reported that elderly people have deficits causing these differences, such as cognitive ability deficits, motor movement, and less experience in technology use, which creates obstacles in adopting technology amongst the elderly and makes technology use for elderly users limited. For instance, it was reported in (Sulaiman & Sohaimi, 2010) that making an emergency calls is mostly use of mobile phone for elderly people. In line with previous studies, we expect elderly users to exhibit scan-path dissimilarities in browsing smartphone applications compared to users of other age groups (hypothesis H1).

2.2.3 Developing the Technology Interfaces for the Elderly

It is very clear from previous studies (e.g. (Chen, 2013), (Stößel, et al., 2010), (Arning, et al., 2010), (Stößel, 2009), (Hawthorn, 2003)) that elderly suffer when using technology applications that designed to meet younger users ability more, and they find learning on how to use technology applications difficult.

How can we increase the usability of technology for elderly users?

As mentioned in the previous sections, low confidence, anxiety, inexperience in technology use and difficult design place barriers to the effective use of technology by elderly. These barriers can be surmounted by at least three ways (Stößel, 2012). The first is by motivating and encouraging elderly users to use technology in order to adapt them into new technology applications designs (Chen, 2013), (Laouris, 2009). The second way is training elderly users on how to use technology, which makes their performance better (Leitão, 2012), (Artis, 2004). The third way is developing devices that better matches elderly users' needs and abilities (Stößel, 2012), (Arning, et al., 2010), (Duval, et al., 2008). It was reported by (Stößel, 2012) that the usability of technology for elderly can be improved by a combination of these ways. Also, in order to find solutions to the difficulty of technology design, the researchers and designers should consider the following two kinds of designs.

Design for All (exclusive), also known as design for human diversity, and social equality concentrates on designing technology with a focus on particular user groups (e.g. the elderly are exclusive), in order to enable them to have equal opportunity to contact with others and in every feature of society (Stockholm, 2009), (Elokla, et al., 2006). It was stated by (Stößel, 2012), and (Duval, et al., 2008) that this kind of design runs the risk of stigmatization and the acceptance of technology will be reduce by the elderly when the focus is on their impairments and physical deficiencies.

Inclusive Design compromises what elderly users need and what other users of different ages need in the same design, where the compromises are not favoured by elderly users or by younger users (Stößel, 2012), (Hawthorn, 2003). Or *Universal Design* (i.e. *transgenerational*, *lifespan design*) means designing technology interfaces without focusing on particular user groups in order to be usable by all people. Previous studies (e.g. (Stößel, 2012), (Elokla, et al., 2006), (Persad, et al., 2006), (Deardorff & Birdsong, 2003)) stated that the universal design might not appropriately address the problems of the elderly with technology use, where the universal designs believe that one design can suit everyone. Several studies (e.g. (Stößel, 2012), (Duval, et al., 2008)) reported that elderly people have difficulty using technology with these designs, where these designs do not accommodate the needs of the elderly, so these designs should be avoided when developing technology.

Table 1 below summarises the relevant issues of age-related impairments on physiological and psychological characteristics to computing devices and our researches.

Table 1. A summary of age-related impairments and their effects on technology use.

No	Impairments	Difficulties faced	Relevant to this research
1	Vision	Reduced vision capability makes the interaction difficult and worse in the following cases: - Small items on visual display (e.g. font, or small distances between interface items) - Smaller screen sizes	Yes
2	Touch	Reduced sensory perception of touch for users increases the task performance error. This will be worse with smaller size content on interfaces. High/Low sensitivity touchscreen response increase error rate.	Yes
3	Memory	Remembering the gestures' shapes and positions on the visual display will influence on users performance. Remembering the steps to perform tasks are difficult. Recognizing the interfaces items based on how it works will not be easy for elderly users.	Yes
4	Attention	Crowded items on the visual display distract users' attentions. Performing dual tasks reduce their focus. Difficult to balance attention on both speed and the accuracy of performing a task.	Yes
5	Control Movement time	The performance accuracy will be reduced when control ability is reduced.	Yes

In order to assist in addressing technology design problems, and to increase the usability and quality of life for elderly people, we conducted a study on users' age-group classification using gestures on smartphones which will let the users interact with technology based on their ability. We suggest to use the user's age-group classification study as a system to let the users interact with the technology based on their abilities that will let the system turn into a particular setting to fit their ability, especially for elderly users. This will lead to customized user interfaces that will increase the usability of smartphone for elderly users (see Chapter 7 for more details on user-age-group classification using touch-screen gestures).

2.3. Chapter Summary

This chapter provided an overall background on the relationship between technology interactions and the elderly in two main aspects. First, the chapter reviewed and discussed age-related changes in sensation and perception, cognitive ability and motor movement ability. These changes are linked to the problems that elderly encounter when interacting with technology and causes disinclination towards the use of technology. Secondly, several aspects of technology interaction have been discussed in greater detail by reviewing technology interaction problems for elderly such as pointing difficulties, complex interface designs, and issues with screen size. This was followed by a review of studies on the attitude and anxiety of elderly towards technology use. In addition, inappropriate technology designs that fail to accommodate elderly users' needs and ability were discussed. Several technology designs; design for diversity, universal design, or compromise design and their suitability for elderly users were discussed.

The next chapter will review existing work most relevant to our studies. In particular, we will review literature on the two interaction methods; eye movement and touch-gesture interactions.

CHAPTER 3

LITERATURE REVIEW

This chapter presents a review of literature usability studies based on eye movement analysis and touch-gestures. A particular emphasis will be on age related usability issues. Section 3.1 will focus on eye-movement tracking whilst Section 3.2 focuses on touch-gesture based studies. We will discuss the advantages of using these two interaction methods to justify our approach to evaluate age-related issues on smartphones and tablets.

3.1. Eye-Movement Tracking

This section discusses the usefulness of using eye tracker systems and review studies from the literature that conducted on visual displays for elderly using eye-movement tracking. An eye-tracker system will be used in our study to track, record, and analyse eye movements of users during their browsing the smartphone application interfaces.

3.1.1 Eye Movement in HCI

Eye movement data can indicate browsing efficiency and difficulty in information processing. Rayner (Rayner, 1998) stated that eye movement data provides important information on the user's behaviour. Based on eye movement data, user's thoughts and intentions that links to user's cognitive processes can be interpreted and inferred by the researchers. Moreover, previous studies have suggested (e.g. (Obrist, et al., 2007), (Cooke, 2006)) to use eye movement data in HCI for using pertinent measures such as fixation duration and number of fixations on interfaces.

Minocha et al. (Minocha, et al., 2005), and Obrist et al. (Obrist, et al., 2007) stated that using eye movement in the evaluation can help discover the relationship between all of the preferences/expectations and visual browsing behaviour, and it provides many of the cues to human behaviour. Several studies (e.g. (Schotter & Rayner, 2013), (Poole & Ball, 2004)) stated that eyes and mind of user are linked when processing information, such as reading. Furthermore, eye movement data can provide much of cognitive information processing that might be useful to enhance the usability of technology interfaces.

A key feature of using eye movement was reported by (Poole & Ball, 2004) in that eye movement data provides practical evidence about the usability of technology. Investigating usability of technology interfaces for users' behaviour will be interpreted based on eye-movement data retrospectively. Jacob and Karn (Jacob & Karn, 2003) stated that interpretation of user's eye movement behaviour is difficult; it is not similar or as straightforward as it is with more usual task performance, durations, or error rates. This kind of research on eye movement is always associated with the nature of the stimuli, and with the method (e.g. search technique) used to collect data from users when browsing technology applications (McConkie, 1982).

Search technique is one of the methods used to collect data from the participants. It is used to find a particular item on the interface that will measure the time spent till a user finds a target (i.e., item). Several studies (e.g. (Jacob & Karn, 2003), and (Goldberg & Kotval, 1999)) stated that an eye-tracker traces a user's attention based on eye movement, and provide information on where the user is focused in relation to a visual display. The meaningfulness of the interface contents can be evaluated, and the interface design will be improved based on the evaluation of eye movement data.

In our researches, we used similar interpretations for eye-movement data that were used in previous studies such as (Al-Wabil, 2009), and (Josephson & Holmes, 2002). These data include scan-paths string-edit, fixation duration, scan-path duration, and saccades amplitude that are explained in Chapter 4. Note that the previous studies were conducted on different populations, technology applications, and on different technology devices.

3.1.2 **Eye Movement Tracking in HCI for elderly**

Concerning technology evaluation using eye movement for elderly users, unfortunately there are not many studies. Fukuda and Bubb (Fukuda & Bubb, 2003) conducted a study on eye movement tracking to investigate the differences in behaviors for elderly users (14 participants aged between 62-74 years old) and younger users (13 participants aged between 13-29 years old). The study was conducted using electronic timetable system on web pages using search task on a PC. The results revealed that elderly users exhibit longer fixation durations, more scan-path duration, and exhibit shorter eye movement length than younger users. They noted that the deficits of visual function for elderly can negatively influence on the visual information processing when interacting with web pages, where small letters and small navigational buttons can disturb the interactions. Their findings also showed an inconvenient navigational structure and an inappropriate web pages design for elderly users and younger. They suggested the necessity of particular consideration for elderly users regarding their needs and ability in using web design. Based on these results, we expect that the interface contents (stimuli) will have a strong effect on the performance of elderly users in scan-paths dissimilarity when browsing smartphone applications (hypothesis H2). Also, we expect that elderly users will take longer time in finding a specific target on the interface and difficulties in browsing applications' interfaces using eye movement than the other age group; this is for local and global information processing difficulties (hypothesis H3).

Another study was conducted on eye movement to investigate the relationship between all of users' expectations and preferences, and visual search behaviour. Minocha et al. (Minocha, et al., 2005) conducted a study on eye-movement in order to understand cognitive processes of users when interacting with the application interfaces of e-commerce websites. They were able to find a relationship and influence between users' experiences on internet and e-commerce websites with their preferences, and expectations of e-commerce interaction using eye movement data.

One of topics discussed in the literature using eye movement is scan-paths string, where scan-paths string were used to investigate the similarity browsing technology interfaces if scan-paths similarity are stimulus-driven and/or participant-driven. Josephson and Holmes (Josephson & Holmes, 2002) analysed scan-paths strings for re-visiting a view on three web pages to measure the scan-paths similarity. A study was conducted on students in the age (average 22.5 years old) with experience average of 9 hours/week in using internet for all participants. The participants were asked to browse web pages as they normally would do for 15 seconds. The results revealed that the main effect was significantly stimulus-driven, with more similar sequences of scan-paths for text-intensive on a news story page than a graphic-intensive on advertising page (i.e., text-driven).

In the same field of scan-paths string, Al-Wabil (Al-Wabil, 2009) conducted a study to examine if scan-paths were participant-driven or stimulus-driven. There were seven participants in the study (two dyslexics and five non-dyslexics, ages are between 22- 40 years) and all of them had at least seven years of experience in using the web. They conducted the study based on revisiting the visual display to find the similarity of scan-paths string using Levenshtein algorithm between first and second view. The results revealed that there was variability in scan-paths for dyslexic people, and similarity between scan-paths string of different participants was higher than the similarity between scan-paths string of the same participants repeatedly exposed to the same stimuli (i.e., stimulus-driven). Also, in the same study, the difficulties at local and global level in information processing for participants were investigated. The study (Al-Wabil, 2009) and (Josephson & Holmes, 2002) have guided our researches to the method and the procedure of conducting an experiments on scan-paths string, local, and global information processing difficulties that have been discussed in the Section 5.1, and in Section 5.2 respectively. To the best of our knowledge we have not come across any study that has conducted on scan-paths string and on information processing difficulties for elderly users on smartphones and tablets.

Unfortunately, there are only few studies concerning technology evaluation using eye movement for elderly users. However, the findings of previous studies reveal important issues to support and add new understanding about age effect on technology use. The researchers in (Igari, et al., 2008) conducted study on eye-movement for elderly people (65-67 years old). Their study aimed to clarify the reasons behind traffic accidents using an indoor simulation compared elderly people with younger people (19- 22 years old). The participants were cycling in a fixed place while the video showed pedestrians on a board opposite to them. The eye movements on the Area of Interests were recorded as follows: looked straight ahead, looked down, right or left hand side, sky, and others. Based on total gaze time, the results showed that elderly people have difficulty in keeping attention on two or more objects. Also, the results showed that the elderly often looked down at the road.

Obrist et al., (Obrist, et al., 2007) conducted a study based on search task to evaluate the usability of the information oriented interactive TV application using eye-tracking for the elderly. They involved users of two age groups: elderly users over 50 years old and users aged (20-30 years old). They focused on how elderly users perceive and interpret a navigation browsing oriented iTV application. Considerably, as they mentioned in their research (see http://mediaresearch.orf.at/), elderly people are the largest group of TV consumers, where the elderly (60 years old and above) in European countries specifically watch TV on average for more than five hours a day. Their findings revealed that interactive TV provides elderly active viewers with the chance to extend their use of the TV similar to the internet. The researchers suggested that the designers of iTV applications should consider the sensory, physical limitations, and cognitive abilities that many elderly people suffer from such as visual deficits, as the elderly have difficulty with font sizes. The elderly took longer time to complete a task than the younger users. (Obrist, et al., 2007).

In summary, most of the previous studies conducted on scan-paths string-edit using search target method and re-visited visual display focused on whether scan-paths are stimulus-driven, text-driven, or participant-driven. However, whether scan-paths of browsing smartphones applications are age-driven or not was not considered. In our studies on eye movement analysis, people from different age groups; 60+, 40-59, and 20-39 years old, three different smartphones screen sizes and nine different interfaces of smartphone applications were used to investigate if scan-paths are age-driven, stimulus-driven or screen-size driven, as well as to investigate difficulties in information processing in local and global level. More details will be given in Sections 5.1, and 5.2 of Chapter 5.

Table 2 below summarises the most similar existing works that have been conducted for elderly users using eye-movement tracking and highlights the areas that needed to be further investigated.

Table 2. A summary of existing work on eye-movement tracking.

Authors	Aim	Applied on	Age groups
(Fukuda & Bubb, 2003)	Evaluated the usability of web-pages	Web-pages on PC	Elderly users (62-74 years old) Younger users (13-29 years old)
(Igari, et al., 2008)	Conducted to clarify the reason behind the traffic accident using *eye-movement tracking*	Indoor simulation	Elderly people (65-67 years old) Younger people (19- 22 years old)
(Obrist, et al., 2007)	Evaluate browsing TV applications	Interactive TV applications	Older users over 50 years old Users aged (20-30 years old)
(Sulaiman and Sohaimi, 2010)	Investigated the obstacles that prevent elderly operate and use Mobile devices to obtain simple interface design of Mobile phone for elder.	Interview Survey questions on user preferred features of mobile phones. Enhanced interface based on finding for mobile phone.	Users in 50 years old and above
Limitations of existing works	Evaluating the usability of smartphones application interfaces	Using eye movement tracking on smartphones application interfaces	Elderly users compared with uses of different age groups.

3.2. Touch-Gesture Interactions

This section reviews a definition, and gestures usefulness for elderly users. In addition, this chapter reviews sets of studies from the literature regarding touch-gestures for the elderly as follows.

3.2.1 Gestures in HCI

Gestures in human communication were defined by Stößel et al. (Stößel, et al., 2010) that they are considered as useful and effective way of nonverbal communication. It was also stated by Bhuiyan and Picking (Bhuiyan & Picking, 2009) that gestures can be used as commands to operate/interact devices via interfaces, or to control smart interface appliances in the intelligent environments. Chen (Chen, 2013) stated that gesture field has become one of the most important current topics of research in HCI.

A key feature of using gestures on touchscreens was stated in several studies (e.g. (Chen, 2013), (Caprani, et al., 2012), (Loureiro & Rodrigues, 2011)) that is their being more intuitive and natural to use, learning ability without prior training, and quick to use in the interaction with technology that can encourage usage on multi-touch devices for the elderly. Number of studies (e.g. (Stößel, 2012), (Caprani, et al., 2012), (Stößel, et al., 2010)) stated that a growing and developing touchscreen technology offers a proper technological use based on gestures for elderly users. The developing on technology e.g. touchscreen could minimize the interaction obstacles, as technology design does not accommodate elderly users' ability, which is considered a challenge for designers. It was reported by Quek et al. (Quek, et al., 2002) that gesture can be used to deliver information or message. For example drawing gestures (e.g. ellipse) can be used to convey information for multi-selection; it can be used to point to the location, orientation, and can be used to operate and select objects. Gestures are used in a wide range of devices (e.g. mobile phone, laptop).

In was reported by Karam and schraefel (Karam & schraefel, 2005) that gestures can be executed on two dimensional (2D) surfaces using finger-based input or a PC mouse. The interaction method used in 2D can be divided into two parts: 1) Indirect input devices that are considered as traditional interaction method, which normally involves devices such as a PC mouse, or a stylus. 2) Direct input devices refer to the direct touch and manipulating the components in user interface. Direct manipulations involve the interaction of touchscreen applications and consist of gestures such as moving, selecting, dragging, sizing, and clicking objects. Several studies (e.g. (Stößel, 2012), (Findlater, et al., 2013)) used 2D devices in their evaluation studies for different populations, and different technology applications.

In our researches, we will conduct touch-gestures' studies on smartphones devices for elderly. In the next Section 3.2.2, several studies will be discussed from literature regarding gesture swiping, gesture accuracy, and user's age-group classifications on smartphones using gesture-based features.

3.2.2 Touch-Gesture Interactions in HCI for the elderly

This section provides a rich review for previous studies that investigated the effects of ageing and screen sizes on technology use in terms of performance efficiency for users on gesture swiping, gesture accuracy, and user's age-group classification using gesture-based applications on smartphones and tablets, as follows:

Gesture Accuracy and Gesture Complexity

In terms of gesture accuracy on touchscreens, there has been only one study conducted on the gesture accuracy for elderly users using large touchscreen size (15-inch). Stößel et al. (Stößel, et al., 2010) conducted a study on a touchscreen (15"- Eizo L353T-C). This screen (i.e., stationary screen) was designed with three different rectangular boundary sizes on large screen size to compensate for the different screen sizes, as follows: 1) small (1.8 inch); 2) medium (3.6 inch); and 3) large (7.2 inch). The three different sizes were chosen to represent different screen sizes as follows: 1) a medium screen size equal to the display of the screen size of an Apple iPhone; 2) a small size designed to 1/4 of medium size; and 3) a large size designed to be four times the medium size.

The above study was conducted on 18 elderly users in the age range 60-71 years old (average age: 63 years), and 18 younger users in the age range 21-33 years old (average age: 26 years). Each participant was asked to trace 42 different shapes of gestures; each gesture was repeated 3 times per screen size. The results of gesture accuracy were analysed based on directional stability and form stability for linear and circle gestures. In the form stability for the linear gestures, the angular deviations were averaged. This is for angles between linear fit and reference line through an orthogonal least square fit. But for circle gestures, the distances from the points to the fitted circle using least square ellipse fitting were calculated. Based on the observation, average deviations and average distances for linear and circular gestures, the directional stability was used to measure how smoothly the task was performed, or how much shakiness in the movement trajectory. In their results, gesture speed was significantly slower across all gesture sizes and complexities for older users. Also, based on form stability, angular deviations were influenced by size and complexity of gestures, but no significant differences due to age group could be observed.

The results of form stability showed a large effect of display size on gesture accuracy and speed. But there is no indication of the effect of age on gesture accuracy. As it was stated in the study (Stößel, et al., 2010) that the younger users were more accurate in the smallest gesture space than elderly users, while in the medium sized space both groups are roughly equal, but in the largest gesture space the elderly users were more accurate than younger users. In line with previous study Stößel, et al., we expect that the elderly would execute gestures slower on smartphones than the younger users (hypothesis H7). Moreover, an influence of complex gestures on age is expected with respect to the gesture speed and/or accuracy (hypothesis H10), also an influence of complex gesture on smartphones' screen sizes is expected with respect to the gesture speed and/or accuracy (hypothesis H11). In addition, we expect that increasing screen size will positively affect gesture speed (hypothesis H12), and gesture accuracy (hypothesis H13). In addition, we also expect an influence of screen size on users when 1) performing gesture swiping (hypothesis H6), and 2) on classifying user's age-group (hypothesis H16).

The work of Stößel, et al. (Stößel, et al., 2010) is different to ours in four areas (details are discussed later in Section 6.2.5 on *Does user-age and gesture-complexity influence the gesture accuracy*?): 1) Stößel, et al. used large touchscreen devices designed into different border sizes; 2) in Stößel, et al. study, the gesture was displayed on the screen for a short period and removed before the participant executed the gesture; 3) in Stößel, et al. study, each participant performed the gestures on each of the three designed sizes of touchscreens; and 4) they analysed their data using average angular deviation between reference line and linear fit and they used the average distances of non-linear least square fitting between the points and the fitted ellipse.

The usability studies on the touchscreen interfaces using gestures for elderly have just begun. There is only one study on gesture based applications for older users on iPod touch. Stößel et al. (Stößel, et al., 2009) conducted a study on a set of 30 single finger gestures on iPod touch device regarding speed and accuracy measurements to find out whether finger gesture interaction could be a proper input method for senior friendly devices. Two age groups were involved in the study: 19 older (60-79 years) and 20 younger users (20-32 years) on iPod touch device to compensate for small touchscreen devices. In addition, each gesture was executed three times for three postures (table, hand, and thumb) to investigate the effect of different device postures on users of different age groups. Posture results showed that thumb operation mode was preferred the least by older as well as younger users. Results of form stability did not show any influence of age on the accuracy of the gesture performance or interaction of age with device posture. Elderly users were slower when performing gestures, as elderly can perform single gesture as correctly as younger users do.

Recently, Motti et al. (Motti, et al., 2013) conducted a literature review research for studies which have been published between the years of 2000 - 2013. They reported that there is only one study conducted for 20 elderly in 60s and 70s years old on touchscreen in literature for these kinds of studies that are discussed in the following studies. Only one study was conducted to evaluate the performance interaction on two different screen sizes: 1) iPad 9.7" to represent a large screen size, 2) iPod 3.5" to represent a small screen size of a mobile device. In their study, each participant was instructed to execute four tasks: dragging, tapping, pinching with panning, and pinching without panning. They aimed to determine the interfaces' problems that elderly users encounter on touchscreens. Based on quantitative and qualitative results, performing tasks on touchscreens were overly easy for the elderly, their performance improved with a week's experience. Also, dragging, pinching, and tapping on the large screen outperformed the smallest screen as they required more than one finger movement on the screen to be performed (Kobayashi, et al., 2011).

Based on the literature review conducted by (Motti, et al., 2013), they found only one study in the literature on the small screen device with landscape orientation, which was conducted by (Nicolau & Jorge, 2012). Nicolau and Jorge examined text-entry performance for 15 elderly in the age range 67-89 years old (average age: 79 years old) on two keyboard sizes of two touchscreens (small: HTC Desire: 3.5", and ASUS Transformer TF101 Tablet: 10.1"). The *quality* of transcribed sentences entered considered the measurement for *input accuracy*, and they measured the *words per minute* input as *speed*. The error rate was measured by using the formula, *Minimum String Distance (required sentence, transcribed sentence) / mean size of alignments x 100*. Based on the qualitative and quantitative analysis, results revealed that error rates were high for elderly users compared to younger users. Also, the input errors were strongly correlated to their hand tremor. The average of error rates achieved on small screen size of 25.97% (SD = 19.72%) was greater compared to large screen size 16.55% (SD = 11.9%). Their findings revealed that elderly users indeed benefit from large screen devices.

Continuing to measure the gesture accuracy for the elderly using gesture swiping, Leitão (Leitão, 2012) conducted a study to measure the accuracy of task performance for elderly users (65-95 years old). In order to measure the *accuracy performance*, they calculated the number of accurate target acquisitions divided by the number of attempts. A game was used, where a helicopter had to be moved (swipe) by finger from the left side toward a destination target on the opposite side of the screen. For tap, they used an insect game, where the participant is required to smash a target insect from grid squares. The results for Tap revealed that the participant's performance was the best when target's size was larger than 14mm of these sizes: (7, 10.5, 14, 17.5, and 21), with 3.5mm space between targets of these spaces: (0, 3.5, 7, and 10.5). Also, they found the horizontal orientation swiping was the best performance (Leitão, 2012).

Also, there was one study designed to involve users with previous experience on touchscreen. Findlater et al. (Findlater, et al., 2013) conducted a study on 20 elderly participants (ages from 61 to 86 years - mean age 74.3) and 20 adult participants (ages from 19 to 51 years - mean age 27.7); where 12 adult participants and 9 elderly reported daily touchscreen use. They used Apple iPads and Apple laptops (Mac OS X 10.7) to examine gesture performance using speed, movement time and index of difficulty for five tasks; pointing, dragging, crossing, and steering. On the touchscreen, they also examined pinch-to-zoom gestures. The results showed that elderly people were slower in using both touchscreen and mouse movements in general when compared to younger users. Also, the error rate decreased on the touchscreen for both age groups. In addition, steering was the most difficult task when using a mouse, while dragging was the slowest gesture on the touch-screen.

Moffatt and McGrenere (Moffatt & McGrenere, 2010) conducted a study to reduce pen-based errors for elderly users using two techniques. First, Bubble cursor for missing: "*landing and lifting outside the target bounds*". Second, Steady Clicks for slipping: "*landing on the target, but slipping off before lifting*"). These two techniques were combined, which have been designed for mouse errors and were used in the study to reduce two of the most common types of pen-based errors for elderly users. In the study, Tablet PC and Wacom Cintiq 12WX pen tablet was used to measure the pen pressure. Two age groups were involved in the study; 12 younger (aged 19-29, average age: 23), and 12 older adults (aged 65-86, average age: 73), where all their participants were novices to pen-based computing. Each participant was instructed to select targets on the screen using a pen-based input device for 324 selection tasks. Based on *likert scale ratings*, the participants ranked the cursors techniques on speed; ease, frustration, and preference. Their results found that older adults exerted 50% more pressure than the younger, and Bubble significantly reduced misses when targets were not adjacent, and slips independent of spacing. The older adults missed significantly more, and were slower than the younger adults. In line with previous studies, an ageing effect on force pressure when executing gestures using finger-based on touchscreen is expected (hypothesis H9).

Piper et al. (Piper, et al., 2010) conducted a study to execute gestures on large screens (e.g. large table-touch) for multi touch gestures. The participants of 20 older adults (aged 60 to 88 years old) were involved in the study using gesture-based interactions on a multi-touch surface (large table touch) for moving cards on the surface and zooming x-ray images. Their results showed that older adults were able to complete a range of touch screen gestures with little difficulty. However, older adults found gestures to resize images and rotate images challenging. Based on the high error rate for elderly in previous studies (Nicolau & Jorge, 2012) and less accurate gesture performance on small gesture space compared to younger users (Stößel, et al., 2010), we expect that elderly users would execute gestures with less accuracy on smartphones than younger users (hypothesis H8).

Gesture Swiping

The most popular method used in the field of gesture swiping is evaluating a user’s performance using agreement scores as described in (Ruiz, et al., 2011) and (Wobbrock, et al., 2009). An agreement score reflects the degree of consensus among users about gestures. For example, Tu (Tu, 2012) conducted a study for 20 elderly (65-77 years old) and 20 younger users (20-30 years old). In their study, they used different kinds of gesture tasks (e.g. delete, pate, zoom-in, and pan). The study was conducted on a HP touch smart tablet tx2 tablet-computer (12.1 inches). The results revealed that both elderly and younger people showed a high agreement score for easier use of some commands, such as, move, next, pan, previous, rotate, select group, insert, zoom-out, and zoom-in. However, there were five commands had different agreement scores (i.e., non-consensus) for both age groups (i.e., select single, open, paste, enlarge and maximize).

Another study conducted by Stößel (Stößel, 2012) using agreement score also for 42 gestures (e.g. maximize window, save file, continuous scroll, play, and pause). The study involved 26 elderly users and 27 younger users. Handheld paper card mock-ups (screen size: 127 x 77 mm) using a USB webcam were used as tools to gather data. A visual trace of participant's fingertips using black paste on the Plexiglas insert that covered the card was used to measure a participant's fingertip movement. Once the participant completed each task, the surface of Plexiglas insert was cleaned and the topmost card was changed by the next task, where each task was explained for each participant. The results revealed that the executed gestures for younger users were more coherent, while there was great diversity within the suggested gestures for elderly users. The highest overall agreement score was measured for selecting a single element from the list. Also, a scroll task has received a relatively high consensus among users, meaning that scrolling can be performed better than other gestures. All previous studies on gesture swiping were not conducted systematically. In other words, the system does not provide the values for movement time (i.e., time spent on the experiment), finger pressure, or gesture lengths in pixels, as our research does. In line with previous studies, an ageing effect on gesture swiping execution is expected (hypothesis H5).

Conducting studies systematically is necessary to understand the difficulty level for the elderly when using technology applications; this is to establish design recommendations for such applications. To the best of our knowledge, we have not come across any research conducted on finger touchscreen to investigate gesture swiping for elderly users (see Section 6.1 for more details about our research in gesture swiping).

Table 3 below summarises the most similar existing works that have been conducted for elderly users using touch-gestures and highlights the areas that needed to be further investigated. To the best of our knowledge, there was no systematic study conducted to examine gesture accuracy and complexity, as well as to examine gesture swiping for elderly users on smartphone and tablets devices.

Table 3. A summary of existing work on gesture-based applications.

Authors	Aim	Applied on	Age groups
(Stößel, et al., 2010)	Investigated whether finger gesture input is a suitable input method	Touch-gestures	Elderly (60-71 years old) Younger users (21-33 years old)
(Kobayashi, et al., 2011)	Evaluated the influence of training for one week on users performance using two different screen sizes: 1) Large screen size (iPad 9.7"). 2) Small screen size: (iPod 3.5").	Performing four tasks on touchscreens: dragging, tapping, pinching with panning, and pinching without panning.	Elderly in 60s and 70s years old
(Nicolau & Jorge, 2012)	Examined the keyboard sizes influence on error rate when typing text using two touchscreens sizes of smartphones: 1) Small smartpone: (3.5"). 2) Tablet large size (10.1").	Entry-text on touchscreen devices.	Elderly users (67-89 years old)
Limitations of existing works	Executing gestures accurately and gesture swiping efficiently on smartphones and tablets devices for elderly users	Gesture based features	Elderly compared with younger users.

User's Age-group classifications Using Gesture-Based Application

This section presents previous studies regarding most similar work to user's age-group classification. We have not come across any research conducted on user's age-group classification using gesture-based features on small smartphones and tablets for elderly users.

In most similar work, Hurst et al. (Hurst, et al., 2008) conducted a study aimed to distinguish between sub movements pointing for data collected from 8 younger adults (20-30 years old), 8 adults (35-65 years old), 7 older adults (70+ years old), and 6 participants with Parkinson's Disease (48-63 years old). This study is considered as the second stage of the study (Keates & Trewin, 2005) that was conducted to examine the effects of age and Parkinson's disease on cursor positioning using a mouse. The specific features they used in the dataset are: 1) number of times if the task was performed correctly, and 2) time movement needed to complete the task. The statistical analysis showed that Hurst et al. were able to distinguish pointing behaviours among users. Based on Decision Tree, the statistical result between adults group vs. older adults group was at 93.8%, adults group vs. younger adults group was at 59.3.8%, and younger adults group vs. older adults group was at 93.3% classification accuracy. In line with previous studies, we expect a possibility of classifying user's age-group based on their abilities when interacting with technology (hypothesis H15).

Our research is different to Hurst et al. (Hurst, et al., 2008) in three main areas. First, they based their measurement on PC mouse movements. Second, they used the following metrics in their study: 1) the movement time needed to complete the task, and 2) the number attempts needed to perform a task correctly. Finally, they used decision tree based on the *observation* in the statistical analysis (see Chapter 7 for more details about our research in user's age-groups classifications).

Sultana and Moffatt (Sultana & Moffatt, 2013) conducted a study to evaluate four algorithms; Decision Trees, Neural Networks, Naïve Bayesian Networks, and Rule Induction for *identifying errors* from sub-movement behaviour using pen-based data for older adults (12 users, age range 65-86 years old), and younger (12 users, age range 19-29 years old). This study is considered as the second stage for the study (Moffatt & McGrenere, 2010) that conducted to reduce pen-based errors for elderly users from sub-movement behaviour. The results of the study in (Moffatt & McGrenere, 2010) were analysed based on *observation* and was discussed in Section 3.2.2 on *Gesture Accuracy and Gesture Complexity*. In order to distinguish errors from sub-movement of older users, there were three training datasets from the collected data, as follows: 1) older users, 2) younger users, 3) all users, and they labelled each data in the all databases as "Error" and "No-Error". In their study, four algorithms were used; Decision Trees, Neural Networks, Naïve Bayesian Networks, and Rule Induction (RI) algorithms for all training datasets. The results showed that each algorithm yielded a classification accuracy rate of around 90%, while the Naïve Bayesian Networks provided the best classification accuracy between all algorithms. Accuracy classification for truly predicted errors for elderly was high compared with other age groups on all algorithms used.

In summary, most of the previous studies were conducted and analysed based on using quantitative and qualitative analysis for behavioural usability metrics on specially designed prototypes of application. Few studies (e.g. (Stößel, 2012), and (Sultana & Moffatt, 2013)) focused on the gesture based applications and touchscreens. We have discussed and differentiated between our research and these previous studies.

The calculation methods used in the previous studies to measure gesture accuracy were different such as number of accurate target acquisitions divided by the number of attempts (Leitão, 2012), and recently, form stability and directional stability (Stößel, et al., 2010), (Stößel, et al., 2009). In our research, the algorithms used to calculate gesture accuracy and the experiment procedures are different compared to the previous studies. In addition, we have not come across any research study conducted systematically on gestures swiping, gesture accuracy specifically on smartphones, as well as on user's age-group classification using gesture-based features on smartphones for elderly users. The user's age-group classification using gesture-based features research has yet to show if the technology of smartphones can classify user's age-group based on user's ability to serve elderly users' needs and abilities (see Chapter 7 for more details about user's age-group classification research).

Table 4 below summarises the most similar existing work that have been conducted for user age-group classification research and highlights the areas that needed to be further investigated.

Table 4. A summary of existing work on user age-group classification and limitations.

Authors	Aim	Applied on	Age groups
(Hurst, et al., 2008)	Distinguished between sub-movements pointing for data collected from participants.	PC mouse.	Younger adults (20-30 years old) Adults (35-65 years old). Older adults (70+ years old) Participants with Parkinson's Disease (48-63 years old)
(Sultana & Moffatt, 2013)	Evaluated the feasibility of using four algorithms; Decision Trees, Neural Networks, Naïve Bayesian Networks, and Rule Induction for *identifying errors* from sub-movement behaviour collected from the participants.	Pen-based interfaces.	Older adults (65-86 years old) Younger (19-29 years old)
The above two studies were analyzed using quantitative and qualitative methods.			
Limitations of existing works	Classifying users' age-groups on smartphones and tablets devices for user-dependant and user-independent scenarios.	Gesture based-features.	Elderly users compared with younger users.

3.3. Chapter Summary

This chapter presented the literature review for two interaction methods used in this thesis; eye movement tracking and touch-gesture interactions. Also, this chapter presented the basic definition for each interaction method, and discussed aspects of usages, which were laid by characterizing what qualifies both of interaction methods in HCI.

In order to increase the usability for elderly users, a number of previous studies recommended to investigate the usability of current technology using eye-movement tracking and touch-gesture interactions. The data from both interaction methods: touch-gestures and eye movement will be interpreted and will help in those recommendations that will advise the designers to consider needs of the elderly in their designs. Several studies were presented and discussed regarding the elderly and their difficulty in interacting with technologies. Subsequently, numbers of previous studies that have been conducted in the usability of touchscreen devices using different applications and tools in the field of HCI were discussed. Based on the previous studies, an efficient performance for elderly users in interfaces' browsing, accurate performance, and the difficulties information processing were presented and discussed.

The next chapter describes the methodology used in our work. The chapter describes the participants, smartphone devices, study metrics, gesture applications, eye movement stimuli, and hypotheses for both eye movement tracking and touch-gesture studies. Experiments, results and discussions will be presented in chapters 5 – 7.

CHAPTER 4

THE METHODOLOGY

This chapter presents the overall methodology used in our experiments. The chapter includes a definition of age groups for people who took part in our researches and a description of the smartphone devices used in our researches. Furthermore, the metrics and hypotheses relevant to both eye movement and gestures studies will also be explained in this chapter. In addition to these, the chapter will provide a description of the eye tracker device, gesture applications and eye movement stimuli that were used in our studies.

4.1. Ages Definition

Age refers to the number of years since birth (Pitt-Catsouphes, et al., 2012), and it is a demographic variable that indirectly predicts the level of disablement in older adults (e.g. physical or cognitive decline). Users of three different age groups took part in our studies: elderly users, middle-aged users (40-59 years old), and younger users (20-39 years old).

Elderly Ages. Glascock and Feinman (Glascock & Feinman, 1980) cited in (Organization & others, 2010) that the definition of older or elderly people can be divided into three categories: First, chronology. Second, change in social role (i.e., retirement from work, menopause status). Third, change in their functional capabilities (i.e., physical characteristics, physiological characteristics). In the conclusion, they reported that the prominent means of defining older age is link to the change in social role, while a chronological definition would be a preferred definition for combining additional definitions; such functional and social definitions.

In terms of age bands, there are no agreed definitions on the age range at which a person becomes old. Moreover, as it was stated in the study (Organization & others, 2010) that the United Nations consider elderly population ages are those people aged 60 years old and over. However, the acceptable definition of elderly or older person in some of developed countries is for the chronological age of 65+ years old. Also, the definition of elderly or older ages at which a person becomes eligible for working retirement pensions has often used the ages of 60 and 65 years old.

Several studies considered people 60+ years old in their studies as elderly (e.g. (Teimourikia, et al., 2014), (Reddy & Chattopadhyay, 2014), (Toyota, et al., 2014), (Stößel, 2012)). However, there were number of studies considered the elderly age is cut-off from 65 years and over (e.g. (Sugawara, et al., 2004)), while some other studies considered elderly people are those who are from 50 years and over (e.g. (Benoit, et al., 2009)). Several studies used the concept as 'elderly' (e.g. (Stößel, 2012), (Kobayashi, et al., 2011)), while many of studies refer to it as 'older' (e.g. (Findlater, et al., 2013). So, in our studies, we will adapt the opinion of Fisk et al. (Fisk, et al., 2009), and to go with the study's viewpoint Stößel (Stößel, 2012) regarding their participants' ages that they gave the definition 'elderly users' for people in age 60+ years old. This will represent the elderly group (60+ years old) in our researches (i.e., EG).

Middle Ages. According to the (Alleyne, 2010) study, the middle ages begins at 35 and ends in the late 50s (specifically 58 years old). Several studies (e.g. (Mui, 2013)) considered people in the range of ages (40-61) years old are middle-aged, while other studies (e.g. (Murata, et al., 2002)) considered the middle-aged are in age range of 50-59 in their study. Based on these previous studies, we will cover all range possible for the middle-age group that are cut-off from 40 to 59 years to represent the middle-age group in our researches (i.e., MG).

The middle-aged users were involved only in the eye-movement tracking research in Section 5.2, whilst they were not involved in the touch-gesture studies due to the difficulty in collecting enough participants. Most of users in this age group have work commitments during the day-time compared to elderly users who normally are in retirement and have flexible time in the day, similar the most of the younger users are university students therefore easier to invite them to participate in the research.

Younger Ages. Several studies (e.g.(Mui, 2013)) considered people under the age of 40 years old are younger ages, while other studies considered the age for younger age group starts from 20 years old (e.g. (Sugawara, et al., 2004)), and ends in the late 20s (e.g. (Murata, et al., 2002). As there are number of studies (e.g. (Stößel, 2012)) that considered people aged from 20 to 33. Based on these previous studies, we will cover all ages possible for younger age group that are in age bracket (20-39) to represent the younger age group in our researches (i.e., YG).

4.2. Research Requirements

4.2.1 Participants Invitations

We followed number of approaches to invite the participants to be involved in our studies, as follows:

1. University of Buckingham website.
2. University public emails to staff and students.
3. Advertise in local newspaper.
4. Some other invited by friends from Buckingham community.

Table 5 review an overall the total number of participants that were involved in the eye-movement tracking and touch-gesture researches.

Table 5. An overall the total number of participants are involved in each chapter.

Age Group	Age Range	Eye-movement number of participants *(Chapter 5)*	Touch-Gesture number of participants *(Chapter 6 and chapter 7)*
Elderly group	60+	22	25
Middle-aged group	40-59	31	-
Younger group	20-39	50	25
Total	**-**	**103**	**50**

4.2.2 Ethical Issues

In this study we followed a number of procedures to meet ethics issues, as follows:

- Data to be collected is depending on the participants' performance tasks using finger touch-gestures and recording eye-movement on smartphone applications. There was no use in our researches for any type of camera for taking pictures for the participants.
- School of Science and Medicine Ethical Approval Form (SSMEC) has been approved
- Consent Form from the participants for using the collected data in our researches was taken, as shown in Appendix C.

- The demographic data that was collected from the participants were transferred into personal hard drive and each participant has given a unique number as shown in Appendix D.
- There were no specific requirements to destroy data after study.

4.2.3 **Demographic Data**

The users have provided us their demographic data regarding their date of birth (year) and their experience in using small smartphones, mini-tablet, and large tablet size as shown in Appendix D. The participants have provided their experience in using applications e.g. Skype, Facebook, email on smartphones and PCs for eye-movement researches. Also, the participants have provided their experience in smartphone use e.g. calling, texting.

4.2.4 **Lessons Learned**

Based on working with elderly people in our researches, we learned a number of lessons that will be useful for new researchers to consider when inviting elderly users to their researches:

1. Researchers should be trained on how to make elderly people not to feel that they always need assistance during conducting the research.
2. Researchers should respect the appointment times of elderly people when inviting them to participant in the research.
3. Researchers should be very patient with elderly when they need more time to perform a task or when they need to repeat an explanation on how to conduct a task.
4. Researchers should consider ethical issues when dealing with elderly people e.g. avoiding issues such as causing stress if the task is perceived be to too difficult to be performed and ensuring that they are not pressured into participating.

4.3. Smartphones and Screen Sizes

Smartphone screen sizes were used in this thesis for the following reasons: 1) they are widely used and available; 2) these devices (i.e. smartphones and tablets) are being continually developed, and have become essential tools used in our daily activities. Also, we used smartphones that are built based on Andriod operating system since they are widely used in most the countries compared with smartphones of other operating systems. For example, according to recent figures the most widely used operating system in smartphones is Android (79.4% market share), followed iOS (15.6%), Microsoft (3.2%), Blackberry (1.9%), and others (0.9%) respectively (Srivastava, 2014).

The criteria for choosing the type of smartphones and tablets depended on the device usability. We have chosen the small smartphone device, and two different tablet devices of two sizes, one that can be handled easily in one hand and the other needs two hands. The three sizes of smartphones used in our thesis are: 1) typical *small* smartphones screen sizes which are between 3 and 5 inches; 2) *medium* size mini-tablets screens are typically 7 inches; and 3) *large* full-size tablet devices are typically 10.1 inches wide or larger.

The three smartphone screen sizes used to examine the influence of screen sizes on users of different age groups using both eye movement and gesture interactions are:

Small - Two small smartphones devices were used in the thesis; one of them was used in gesture experiments and the other one was used in eye movement experiments. Selection the small smartphone for each research depended on the availability of the device at that of conducting the experiments. The devices we used:

1. *Samsung Galaxy Ace S 5830* **-** dimensions 112.4 x 59.9 x 11.5 mm, screen resolution: 320 x 480 pixels, screen size 3.5 inches – this device was used in *gestures* studies.
2. *HTC wildfire* **-** dimensions 106.8 x 60.4 x 12 mm, screen resolution: 240 x 320 pixels, with screen size of 3.2 inches - this device was used in *eye-movement* studies.

Medium - *Samsung Galaxy Tab 2*, dimensions 193.7x122.4x10.5 mm, screen resolution 1024 x 600 with screen size 7 inches - this device was used in *gestures* and *eye movement* studies.

Large - *Samsung Galaxy Note 10.1*, dimensions 262x180x8.9 mm, screen resolution 1280 x 800 pixels. Due to the challenge in collecting sufficient number of participants we will use this device only in *eye-movement* researches but not in touch-gestures researches.

4.4. Hypotheses

Previous chapters highlighted the need for systematic studies that analysed eye movements and touch-screen gestures to investigate the effects of user-age on interactions with modern smartphones. Such studies are required to gain a better understanding of the difficulties faced by elderly when using modern smartphones and tablet devices. To the best of our knowledge, we have not come across previous systematic studies that analysed eye movements and touch-gestures to investigate the effects of user-age on interactions with modern smartphones.

The following hypotheses have been derived based on previous literature and background knowledge of technology use for the elderly to guide our empirical investigation:

H1: Elderly users have high scan-paths dissimilarity when browsing smartphone applications interfaces compared to other age groups. An ageing influence on scan-paths dissimilarity is expected when browsing smartphone applications e.g. Skype, Facebook, email.

H2: The stimuli of smartphone applications interfaces will have a strong effect on elderly performance when browsing smartphone applications interfaces than the influence of smartphone screen sizes. Scan-path dissimilarity of elderly users when they browse smartphone applications interfaces is expected to be stimulus-driven effect than screen size-driven.

H3: Elderly users will have local and global information processing difficulties compared to other age groups. An ageing influence on eye movement regarding recognising items promptly and easy browsing structure is expected with respect to local and global processing measured by fixation duration and scan-path duration.

H4: Elderly users have greater difficulties in executing eye-movement on small screen sizes compared to other age groups. An effect of screen size, measured in terms ratio of saccades, on users' performance is expected, specifically for elderly.

H5: Elderly users have greater difficulties in performing gesture swiping compared to younger users. An ageing effect on intuitive gesture swiping is expected.

H6: Screen sizes have greater influence on users' gesture swiping performance. An influence of screen size on users when performing gesture swiping is expected.

H7: Elderly users execute gestures on smartphone at a slower speed than younger users. An ageing influence on gesture performance speed is expected.

H8: Elderly users execute gestures on smartphone less accurately than younger users. An ageing influence on performing accurate gestures is expected.

H9: Elderly users will exert more finger force pressure when performing gestures than younger users. An ageing influence on finger force pressure when executing gesture is expected.

H10: Complex gestures can influence largely on elderly users performance than younger users. An influence of complex gestures on age with respect to gesture speed and/or accuracy is expected.

H11: Screen sizes have greater influence on the execution of complex gestures. An influence of screen size on the execution of complex gestures in terms of gesture speed and/or accuracy is expected.

H12: Gesture performance efficiency increases when increasing smartphone screen size. An influence of screen size on gestures performance speed is expected when performing gestures accurately.

H13: Gesture accuracy increases when increasing smartphone screen size. An influence of screen size on gesture accuracy is expected.

H14: Force pressure increases when decreasing smartphone screen sizes. An influence of screen sizes on the force pressure when executing gestures on smartphone is expected.

H15: Users' age-groups can be classified using touch gesture based features. Touch gestures based features are expected to be linked to specific user age-group making it possible to use them as discriminant features to classify a user's age-group.

H16: Screen size has an effect in user's age-group classification based on touch-gesture features. An effect of screen sizes on user's age-group classifications using gesture-based features is expected.

The hypotheses from H1 to H4 will be examined in two eye-movement studies: The first research will investigate scan-path dissimilarities of browsing smartphones and tablets applications interfaces for elderly (see Section 5.1 for more details about experiment's contents and results). The second research will investigate information processing difficulties at both local and global level (see Section 5.2 for experiments and results). The hypotheses related to the gesture swiping H5 and H6 investigate the effects of age and screen size influence on user's performance (see Section 6.1 for more details about experiment's contents and results). The hypotheses H7 – H14 concerning gesture accuracy and complexity investigate the effects of age and screen size influence on user's performance (see Section 6.2 for more details about experiment's contents and results). The hypotheses H15 & H16 concerning smartphone user's age-group classification using gesture-based features investigate the possibility of classifying user's age-group, and investigates the effect of smartphone's screen size on user-age-group classifications (see Chapter 7 for more details about experiment's contents and results).

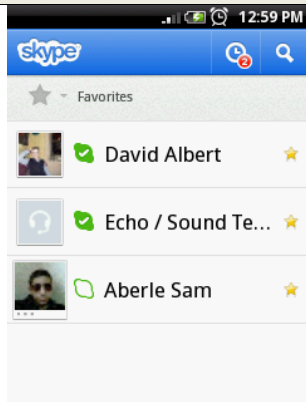
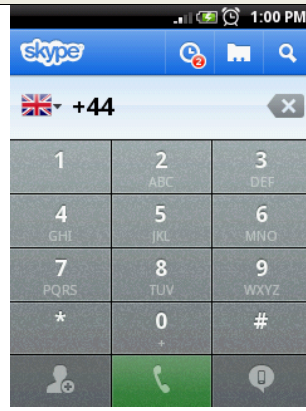
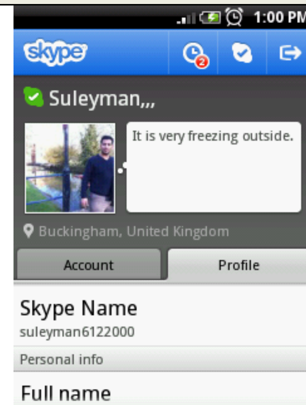
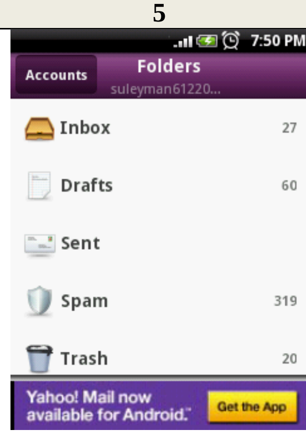
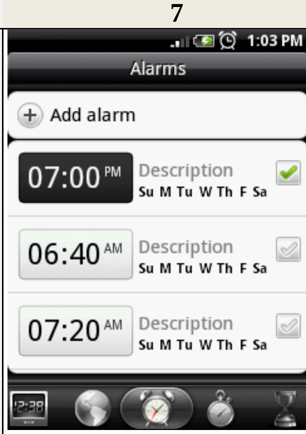
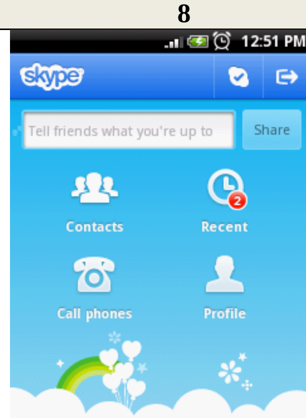
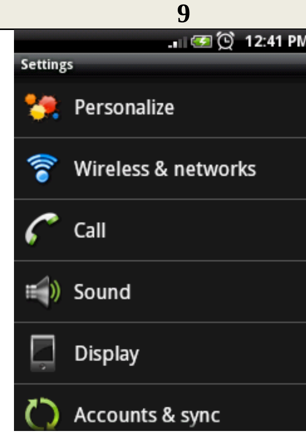
4.5. Eye-movement Stimuli

Eye-movement experiment consists of nine interfaces of smartphone applications e.g. Skype, Facebook, email. These applications were chosen as they are common applications on smartphones and are widely used by people of all ages. We note that recently, several studies (e.g. (Minocha, 2013), (Quinn, et al., 2011)) used social media network (e.g. email, Facebook, Skype) to evaluate the influence of these social media applications on ageing behaviour in order to alleviate elderly from social isolation, and to enhance their quality of life.

Each of the nine interfaces of smartphones' applications has two experiment groups, EXP1 and EXP2. As shown in Table 6, most questions in EXP1 are about the interfaces contents of smartphone applications' that are not well known or used infrequently by users (e.g. locate the button that will show a list of contacts) compared to EXP2 questions, which are about very common and most popular interfaces contents on smartphones applications. For example, "locate the button that will show a list of contacts" is used relative infrequently compared to "locate the 'exit' button". These two experiments were conducted to find out if the user can recognise the most popular interfaces contents (targets) on smartphones applications interfaces in faster time in EXP2 than in EXP1. This is to explore the influence of stimulus and information processing difficulties on users' performance when browsing smartphone applications interfaces.

Following Broder's (Broder, 2002) recommendations on finding specific information/target on a web page, questions/tasks on each application were carefully designed and have only a specific answer. Each participant is instructed to find specific target on smartphones applications interfaces, where this method is called search method (Jacob & Karn, 2003) (see Section 3.1.1 for more details on search method), we will use this search method to examine the time that the user needs to recognise the interface content, and also looking at the device and finding the needed target is considered as the first point of interaction between the user and the application interface. Table 6 shows the questions/tasks that were posed to the participants of each age group on small smartphone (screenshots of the same application interfaces on the mini-tablet and large tablet size are shown in Appendix, E.1: Figure 31-Figure 39, and Appendix, E.2: Figure 40-Figure 48 respectively).

Table 6. Experiment questions and applications interfaces for EXP 1 and EXP 2.

App no	1	2	3
Apps			
EXP 1	Locate the user who is not online.	Locate the Backspace button.	Locate the button used to change your current status to be visible
EXP 2	Locate the image of David Albert.	Locate the Numbers Field.	Locate the account holder's Picture.
App no	**4**	**5**	**6**
Apps			
EXP 1	Locate the number of incoming messages	Locate the number of deleted messages.	Locate the delete image button.
EXP 2	Locate the account holder's name.	Locate the number of new messages.	Locate the Share photo button.
App no	**7**	**8**	**9**
Apps			
EXP 1	Locate the active alarm.	Locate the button that will show a list of contacts.	Locate the button to view Wireless and networks settings.
EXP 2	Locate the button to add a new alarm.	Locate the 'exit' button.	Locate the button that lets you change Sound settings.

4.6. Eye-movement Metrics (features)

Various eye-movement metrics (e.g. fixation durations, scan-path durations, and saccades amplitude) have been used in previous studies on HCI (e.g. (Takeuchi & Habuchi, 2007), (Cooke, 2006), (Jacob & Karn, 2003)) to provide an insight on the link between eye movements and cognitive information processing. The eye-movement metrics that have been used in our research are discussed in the next sections. Figure 3 displays an example of fixation duration, scan-path duration, and saccades amplitude metrics as produced by the eye-tracker system. Increasingly, eye tracking systems are being used in visual display and HCI studies to evaluate technology design for users with expectations, preferences, and experiences (Andrienko, et al., 2012), (Minocha, et al., 2005).

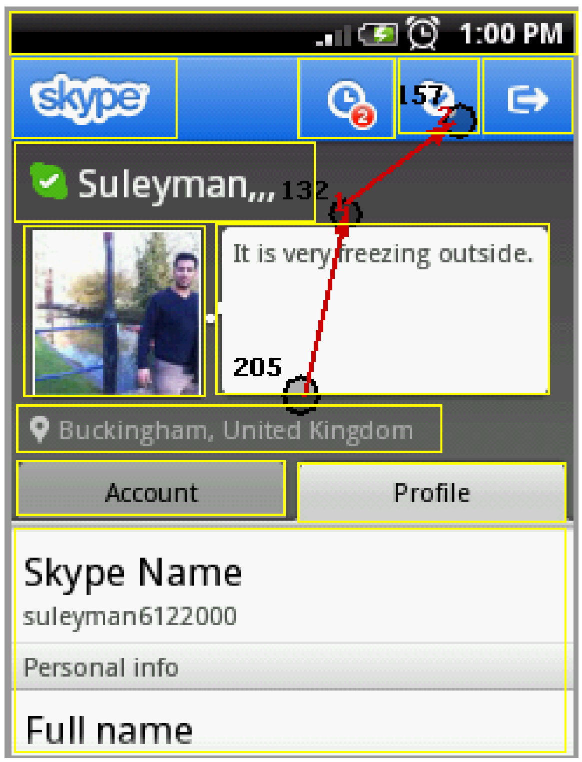


Figure 3. Visual output of eye-tracking metrics. The circles are tagged by its fixation time in milliseconds, saccades amplitude is represented by the arrows red between fixations.

Our experiments use five metrics to measure a user's visual attention on smartphone application interfaces. These metrics are explained below.

4.6.1 **Fixation Duration (FD)**

Measures the amount of time the eyes are focused on a specific item on the screen (Cooke, 2006). FD measures the user's difficulties in local information processing (Al-Wabil, 2009), where a longer FD indicates higher difficulties in locating and recognising a target on the smartphone applications interfaces (Fukuda & Bubb, 2003). FD is measured in milliseconds.

4.6.2 **Scan-Path Duration (SPD)**

A scan-path is a sequence of all fixations and saccades across a visual display (Cooke, 2006), (Rayner, 1998). SPD measures difficulties in global information processing on interfaces (Al-Wabil, 2009), where a longer SPD indicates less efficient scanning and browsing (Poole & Ball, 2004), (Goldberg, et al., 2002). SPD is measured in milliseconds.

4.6.3 **Scan-Paths String**

The applications interfaces of the smartphones were divided into set of regions represented by letters starting from letter "A" depending on the number of regions of interest on the screen. Eye tracker generates the scan-path string by tracing the participant's eye movement that visits different regions to find a given target (Al-Wabil, 2009). Scan-paths string refers to a set of regions represented by letters given to the visited regions on a screen until a target is found (Josephson & Holmes, 2002). This metric used to measure the scan-paths dissimilarity in browsing interfaces among participants for each age group.

The scan-paths dissimilarity were calculated based on the distances between all pairs of scan-paths for each of the nine interfaces of applications among all users of each age group on each smartphone screen size separately. The algorithm used to calculate the distances between pairs of scan-paths is Levenshtein algorithm which finds the minimum cost to transform one string of scan-paths into another string, where a large distance value indicates high dissimilarity. Table 7 (Duchowski, et al., 2010) illustrates the calculation of Levenshtein distance for the two strings S1= {AFBFFDCDF}, and S2= {ABCFEFFGDC}, where the highlighted background number in corner of the table shows the distance between these two strings.

Table 7. Example of Levenshtein distance calculation.

	A	F	B	F	F	D	C	D	F
A	0	1	2	3	4	5	6	7	8
B	1	1	1	2	3	4	5	6	7
C	2	2	2	2	3	4	4	5	6
F	3	2	3	2	2	3	4	5	5
E	4	3	3	3	3	3	4	5	6
F	5	4	4	3	3	4	4	5	5
F	6	5	5	4	3	4	5	5	5
G	7	6	6	5	4	4	5	6	6
D	8	7	7	6	5	4	5	5	6
C	9	8	8	7	6	5	4	5	6

The formula of Levenshtein algorithm is defined in equations (1) and (2) below:

$$A[i][j] = \min\begin{cases} A[i-1][j\quad] + 1 \\ A[i\quad][j-1] + 1 \\ A[i-1][j-1] + C(i,j). \end{cases} \tag{1}$$

The first and second terms of equation (1) handles the costs of deletions and insertions, and the third term handles substitutions, with:

$$c(i,j) = \begin{cases} 0, S1\,[i-1] = S2[j-1] \\ 1, otherwise. \end{cases} \tag{2}$$

The Levenshtein distance, "LDIS", between the participants on each application interface is presented by "A" in equation (1).

4.6.4 **Saccade Amplitude (SA)**

Saccades occur when the eye moves from one fixation to another fixation (Cooke, 2006), (Rayner, 1998). Large length of saccade amplitude gives more meaningful cues and browsing, and less task difficulty (Goldberg, et al., 2002). SA is measured in terms of visual angle degree.

4.6.5 **Ratio of saccades (RS)**

It is a measurement derived from the saccade amplitude and scan path duration - RS is the total length of SA divided by SPD. A larger RS indicates more meaningful searches and efficient browsing. Ratio of saccades is used to examine the effects of screen sizes on browsing efficiency and application interfaces usability for all age groups.

4.7. Eye Tracker Device and Experiment Set up

The eye tracker device used in the eye movement experiments is the *Eye-link 1000 desktop device mounted with an IR illuminator on the right* (SR_Research.Ltd, 2010). The eye tracker device is used to trace and record users' eye movements on the visual display of smartphone application interfaces. Also, another PC screen was used to display the question for each target of interfaces on the smartphone applications.

The eye tracker device was placed under a visual display unit (a PC screen), whilst the participant fixed his/her chin and head on a chinrest – a chinrest was used to avoid head movement during the experiment – at a distance of approximately 55-60 cm between the user and eye tracker as recommended by (SR_Research.Ltd, 2010), and as used in the study (Nettleton & Gonzalez-Caro, 2012). The chinrest was centred on, and horizontally aligned with the monitor, while participants remained seated in a comfortable position during the experiment. Figure 4 show a graphical illustration of the eye tracker and participant.

Once seated for an experiment, the first task was to perform a camera adjustment which included a calibration and validation for the participant. A 9-point grid calibration and 9 validations with the eye tracker were conducted. Calibration and validation involved a user to follow nine white circles on the screen with their eyes, and match between the calibration and validation. A re-calibration and a re-validation were carried out until a good validation was achieved.

Figure 4. An example of calibrating the eye-tracker system for a participant.

After successful calibration and validation, the system will start to display the nine interfaces of smartphone application screenshots as images, one-by-one, to the participant. On each image view, another calibration is performed to check the user's current eye position with the one that was taken at the initial calibration to make sure the accuracy of gaze quality remains high, this is to start track and record to eye movement by the system. The question for each target on the displayed application interface was presented on another screen placed next to and in parallel to the experiment's screen. Each task ends when the participant presses the space bar of the experiment's device keyboard, or the eye tracker ends by itself if the participants could not find the target in 30 seconds. Once a user finds the target on the screen and hit the space bar, the system will stop tracking and recording the participants eye-movement for that particular task (SR_Research.Ltd, 2010). Then the next screenshot will be displayed to continue the experiment.

4.8. Gesture Applications

Gesture study consists of eight single-line gesture shapes as illustrated in Figure 5. The eight gestures were implemented on a small smartphone and a mini-tablet device (see

Section 4.2 for more details about screen sizes). These gestures were identified by Microsoft (Microsoft, 2009), and they are similar to the single-line gestures that were used in (Akl & Valaee, 2010), and (Stößel, et al., 2009).

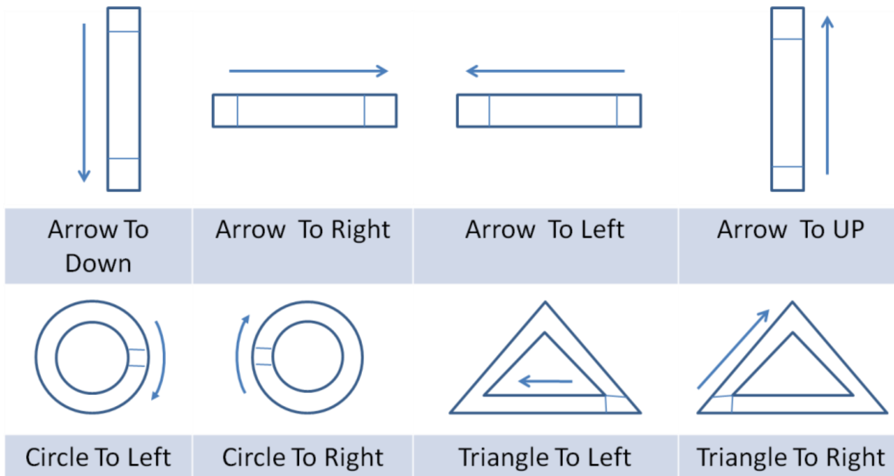


Figure 5. Gesture Applications of eight shapes.

The single-line gestures were chosen for the following reasons: 1) Single-finger gestures were preferred by older users; 2) it was stated by (Stößel, 2012) that multi-touch based interaction in a mobile environment is not necessarily used and perceived by younger users as most natural and intuitive; 3) it was recommended by Stobel (Stößel, 2012) to avoid designing multi-finger gestures; 4) longer length gestures offer strong possible results when calculating gesture accuracy for having many points of the coordination (x,y) along the trajectory to match the reference data with the data obtained. This will not be available in other kinds of gestures such as tap gesture, pinch gesture that have short length of gesture. Longer length gesture will provide enough information about finger movement behaviour that includes accurate performing gestures, force pressure, movement time, etc.

4.9. Gesture Metrics (Features)

A total of seven metrics were used in our gesture studies to evaluate ageing effects on smartphone usability. Four metrics were used in the gesture swiping research: force pressure (i.e. FP), movement time (i.e. MT), gesture swiping speed, and the ratio of speed to finger pressure. Five metrics were used in the gesture accuracy and complexity research (note that some of metrics were used in both studies): force pressure (i.e. FP), movement time (i.e. MT), gesture accuracy speed, gesture accuracy, gesture complexity. Figure 6 and

Figure 7 illustrates how these metrics are calculated for an example gesture, while the rest of the chapter explain each metric in detail.

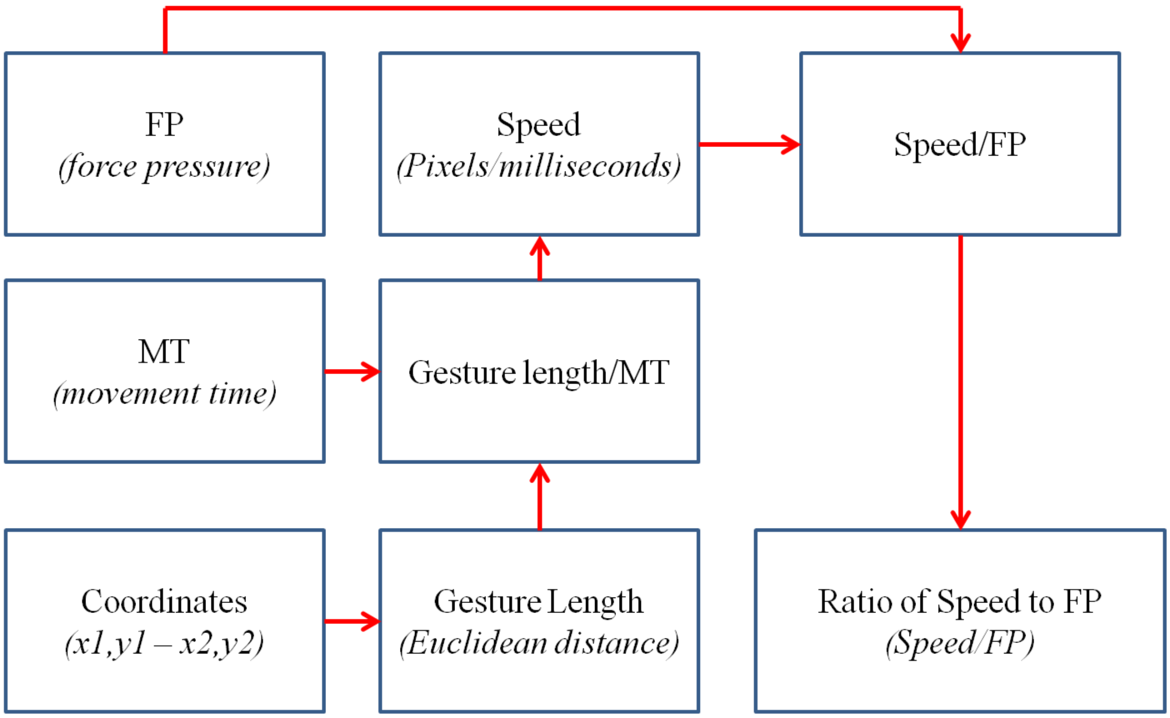


Figure 6. Gesture swiping metrics used in the research.

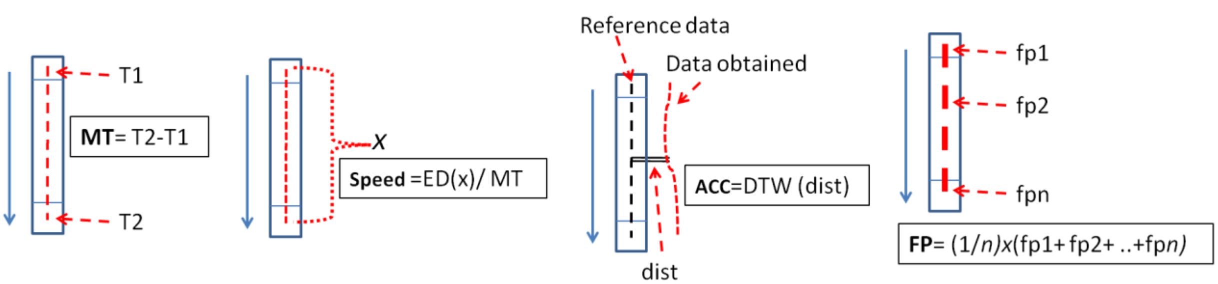


Figure 7. Illustration of how gesture metrics are calculated for the Arrow to Down gesture.

We designed our own smartphone applications to display the eight gestures (see Figure 5 and Figure 25) to capture relevant data for gesture accuracy and gesture swiping studies. All gesture applications used in our experiments were implemented in Java for Android Version: (4.2.1). The applications trace a participant's finger movement on the surface of smartphones and record time-stamps, finger pressure, and the coordinates (x,y) for each point on the trajectory as the user performs the gesture. The seven metrics used in the gestures studies reported in Chapter 6 and 7 are as follows:

4.9.1 Movement Time (MT)

MT is the task completion time which will be used to measure time spent on the task to examine the effect of age on gesture-based applications on smartphones and mini-tablets. MT is the time spent between finger-down and figure-up for gesture accuracy research or between finger-down and hit the target for gesture swiping when executing a gesture (Findlater, et al., 2013), (Farage, et al., 2012), and (Stößel, et al., 2010), and it is measured in seconds. This metric was used in gesture swiping, and gesture accuracy studies.

4.9.2 Finger/Force Pressure (FP)

The smartphone application traces a user finger on the surface/screen of smartphones, can measures the force pressure exerted at each point (i.e., (x,y) coordinate on the screen) on the trajectory when performing gestures. Finger pressure is used to measure and compare the amount of force pressure exerted by younger and elderly users when performing gestures. Finger pressure is used to examine the influence of age in performing gestures across two screen sizes, and then to investigate if screen size has influence on smartphone and mini-tablet usability. This metric was used in gesture swiping, and gesture accuracy studies.

As it was reported in previous studies, hard pressure on the technology contents (e.g. keyboard keys)- specifically on small contents - indicates lower sensory and perceptual sensitivity of the body against a surface, more so for elderly (Farage, et al., 2012). Elderly users found pen-based interfaces on tablet PC (laptop 12.1') tiring and exerted 50% more force pressure compared to younger users (Moffatt & McGrenere, 2010). Moreover, the meaning and the interpretation of the touch behaviour is left to the receiver of that touch (Gao, et al., 2012). Based on previous studies, we supposed that a lower force pressure value of finger on smartphone touchscreen indicates the user's increased sensory perception of touch, which indicates a positive usability of the technology. In line with the previous studies, an influence of screen sizes on the force pressure for users when executing gestures on smartphones is expected (hypothesis H14). To the best of our knowledge, we have not come across any research that used finger-based touchscreens to measure finger pressure to examine smartphone usability for elderly.

4.9.3 Gesture Swiping Speed

The speed in gesture swiping research is calculated by dividing the gesture swiping length (total distance in pixels) by MT (milliseconds). Gesture swiping speed is used to measure user's efficiency when executing gesture swiping on smartphones and mini-tablet.

Based on speed, we also investigated the surface space influence on users' performance for the orientation swiping. For this, we divided the results into two parts, 1) vertically orientation, which consists of swiping down, and swiping up, 2) horizontally orientation, which consists of swiping left and swiping right.

4.9.4 Ratio of Speed to Finger Pressure (RSTFP)

Ratio of speed to finger pressure is gesture swiping speed divided by FP of gesture swiping. This metric investigates the ratio between a user's efficiency - measured based on speed, and the force pressure exerted. In other words, this metric is used to measure the smoothness of gesture swiping on smartphones. A high ratio indicates a smooth gesture performance. This metric was used only in the gesture swiping research.

4.9.5 Gesture Accuracy (Acc)

Gesture accuracy is used to measure a user's ability perform gestures accurately. The calculation for the gesture accuracy was built based on the distances between the optimal path (reference data) of a gesture and data obtained from the user's gesture. The reference data is from the centre of starting box through the middle of the path to the centre of ending box; all the reference data are invisible to the user. For example, the MT in Figure 7 illustrates the starting point of the box (i.e., T1) and ending point of the box (i.e., T2), where the discrete red line in the path represents the reference data that are invisible to the user. The reference data for each of the circles and triangles was designed from the centre of the box through the middle of the path to the centre of the same box, as we have only one box for each of these gestures. Short distance between the reference data and data obtained indicates high accuracy in gesture performance.

Gesture accuracy was calculated using Dynamic Time Warping (DTW) to examine the effect of age in executing accurate gestures on smartphones and mini-tablets, and to examine the effect of screen sizes on users of different age groups. DTW measures the distance between two different sequences of different lengths (Keogh & Ratanamahatana, 2005). Normalization was applied for all participants across all screen sizes, and then the average and STD of accuracy for each age group was calculated by using 2-way ANOVA test.

4.9.6 Gesture Speed

The speed in our gesture accuracy research is used to measure the efficiency of users of different age groups across two screen sizes, and to investigate if screen size has an influence in performing accurate gestures on smartphone/tablet (see e.g. (Farage, et al., 2012), (Stößel, 2012), and (Stößel, et al., 2010)). This metric was used only in the gesture accuracy research.

The speed in our gesture accuracy research is calculated from gesture lengths (total distances in pixels) divided by MT (milliseconds). The gestures lengths for arrow to down, arrow to left, arrow to right, and arrow to up were calculated using Euclidean distance between the start point (x1, y1), and end point (x2, y2). While the total gestures lengths for circle to left, circle to right, triangle to left, triangle to right were calculated using Euclidean distance also to find the distance between any two points on the trajectory from start point (x1, y1), until the end point (x2, y2); this is because there are curves and corners in these gestures.

4.9.7 Gesture Complexity

The complex movement pattern of gestures is considered as independent variable to measure the influence of complex and non-complex gestures on user’s performance. This metric consists of two parts: simple gestures (i.e. non-complex) and complex gesture for having curves and corners in the complex gesture. The eight gestures were divided into two parts: non-complex (i.e., simple gestures) and complex gestures. The circles and triangles are considered as a complex gestures based on corners and curves used in these four gestures (i.e., circle to left, circle to right, triangle to left, and triangle to right). While the other four gestures (i.e. arrow to down, arrow to left, arrow to right, and arrow to up) are considered as a non-complex gestures as it was executed in (Stößel, et al., 2010). This metric was used only in the gesture accuracy research.

The gesture complexity was measured based on two kinds of metrics; gesture speed, and gesture accuracy. Each was conducted separately to examine the effect of complex and non-complex gestures on age and screen sizes using these two metrics. The difference area between what we did in our research and the one by (Stößel, 2012) is that they used velocity and form stability in examining complex gestures, whereas we conducted our research on gesture speed and gesture accuracy on complex gesture and non-complex gesture to measure the gesture complexity influence on user performance.

In order to calculate the gesture complexity, we took the following steps: First, grouping the participants into two age groups. Second, the gesture speed/gesture accuracy data were divided into two parts based on complex gesture and simple gesture. Third, the statistical analysis for each age group was calculated using ANOVA.

4.10. Chapter Summary

This chapter described the methodology used in the study in five main aspects. First, it presented a definition of age groups used in the thesis. Secondly, the chapter gave details of the smartphones and tablets devices used for experiments in the thesis. Third, a set of hypotheses were posted for our investigation that will provide a theoretical and an empirical account of visual search behaviour and touch-gesture interactions for elderly users on smartphones and tablets to the existing body of literature. Fourth, in this chapter there were review and describe for eye movement stimuli and gesture applications that we designed our experiments based on them. Finally, the various metrics that will be used to analyse usability issues were defined. The results of these metrics will extract the level of usability of smartphone interfaces for elderly users compared to other age groups.

The next three chapters are devoted to present and discuss the results of the various experiments we conducted. Sections 5.1 and 5.2 in Chapter 5 will address the research question Q1 to cover hypotheses H1 – H4 regarding scan-paths dissimilarity and difficulties in information processing at both local and global level. The results of two studies conducted using eye movement and smartphones applications will be the basis of this chapter. Section 6.1 of Chapter 6 will address the research question Q2 for hypotheses H5 -

H6 regarding the influence of ageing and screen sizes of smartphones on performing gesture swiping intuitively, whilst Section 6.2 addresses the research question Q3 for hypotheses H7 - H14 regarding the effect of ageing, screen sizes, and gesture complexity in performing accurate gestures on smartphones. Chapter 7 will address the research question Q4, which is linked hypotheses H15 - H16 regarding the possibility of classifying user's age-group based on user's ability to use gesture-based features on smartphones. All research questions were posed in Section 1.2, and all the hypotheses were described in Section 4.4.

CHAPTER 5

EYE MOVEMENT INTERACTIONS ON SMARTPHONES FOR ELDERLY USERS

This chapter conducts exploratory studies of smartphone interface interaction behaviours for elderly users using eye movement. Two studies having been conducted using nine interfaces of smartphone applications to address the research question Q1 described in Section 1.2 which is relevant to hypotheses H1 - H4. The first research was conducted to investigate scan-paths dissimilarity in browsing smartphone applications based on string-edit method to compare performances of elderly users with younger users. The second research was conducted to investigate difficulties in information processing at both local and global level for elderly users compared to middle-aged and younger users. Chapter four presented relevant details on age groups, smartphone devices, the eye-tracker system, the stimuli and the various metrics will be using here.

A particular interest of age in these two studies is elderly users. Users of other age groups, i.e., middle-aged and younger users, were involved in these two studies in order to understand the difficulty level for the elderly compared to users of other age groups.

In addition to investigating the effects of age, three sizes of smartphones/tablets were used in the two aforementioned studies to examine the screen size influence on users' interface browsing effectiveness/characteristics. In terms of smartphone usability, we have not come across any other research conducted on smartphones/tablets applications browsing for elderly users using eye movement tracking. Therefore, the outcomes of these studies will add to our understanding of the particular needs of this user population that will have implications for the design of effective interface structures for modern technology.

5.1. Browsing Effectiveness on Smartphones

In this section we will use scan-paths dissimilarity to investigate the effects of age and screen-size on browsing smartphone applications. A scan-path is considered as one of the most important metrics captured by eye tracking systems. The investigation was performed on three smartphone screen sizes; small, medium, and large. Levenshtein algorithm is used to calculate the distances between pairs of scan-paths string for elderly users and younger users (see Section 4.6.3 for more details on scan-paths string-edit).

5.1.1 Overview of Experimental Hypotheses

The specific expectations that were examined in this experiment are hypotheses H1 and H2 regarding scan-path dissimilarity browsing for elderly, and screen sizes influences on users' performance (see Section 4.4 for more details on the relevant hypotheses).

5.1.2 Methodology

Experiment Structure

Each smartphone size has two experiments (EXP1 and EXP2), and each experiment is conducted using participants from two age groups (YG, and EG). A participant was involved in only one smartphone screen size and in one experiment to avoid any influence of familiarity on the participant's performance. Figure 8 illustrates how experiments and different groups of participants are organized.

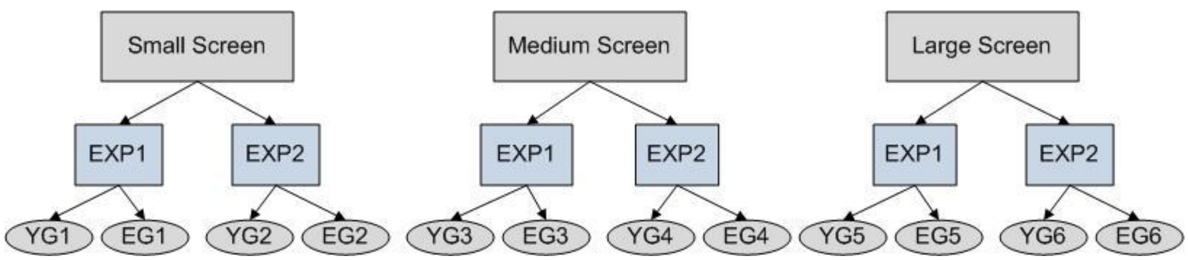


Figure 8. Organization of smartphone experiments and age groups.

Apparatuses

This research used the eye tracker, and smartphones of three screen sizes; small, medium, and large screen sizes. Specific details of the smartphones and the eye tracker device are in Section 4.2 and Section 4.7 respectively.

Participants and Stimuli

In total, 32 participants took part in this exploratory experiment as described in Table 8. The participants were selected from different age groups and include university students, university staff, and people from the local community. Each participant was asked to fill a demographic data form regarding age group, and their average experience in using applications; Skype, Facebook, and email, on smartphones/tablets and on PC (a data form is shown in Appendix-A). The average experience of a participant was calculated based on their experience in using Skype, Facebook, and email on smartphones/tablets. For example, if a participant has 2 years of experience in using a smartphone for Skype, Facebook, and email, the average experience of the smartphone applications for this participant is 2 years. The participant's experience of using smartphone applications for Skype, Facebook, and email were averaged based on two age groups as shown in Table 8. Figure 9-a shows the average experience of application use for the two age groups on each of the three smartphones screen sizes, whilst Figure 9-b shows the average experience of application use for the two age groups on PCs. The nine interfaces of smartphone applications used as stimuli were explained in Section 4.5.

Table 8. Participant details.

Age Group	No. of participants	The average experience of applications use on smartphones/tablets
EG	16	0.18 years
YG	16	0.76 years
Small smartphones	12	0.57 years
Mini-tablet	9	0.39 years
Large-tablet	11	0.46 years

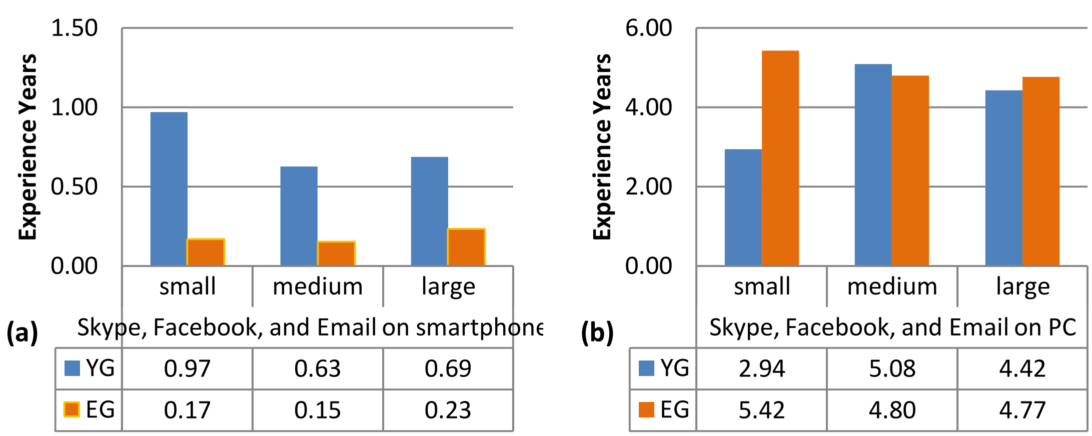


Figure 9. Average experience of applications use: a) on smartphones/tablets, b) on PCs.

5.1.3 **Experimental Design and Procedure**

Each of the nine interfaces of applications has two experiment groups (EXP1 and EXP2), and each has different questions (i.e., targets). The experiment procedure for this research was described in more details in the Section 4.7.

In order to investigate if scan-paths dissimilarity are age-driven, and to ascertain whether scan-paths dissimilarity are either smartphone screen size-driven or stimulus driven, we followed two steps to calculate the mean and standard deviation (STD) of scan-paths dissimilarity for each age group on each screen size. First, equation (3) shows how the distance between pairs of scan-paths on one interface of applications, each from different participant, is calculated. We use the scan-path of the first participant (i.e., scan-path(YG1(participant 1))) and compare it with the scan-path of the same interface of applications, but from the second participant (i.e., scan-path(YG1(participant 2))), and then compare the scan-path of first participant with the scan-path of third participant, and so on to find the distance between all scan-paths among all participants of that age group for that application interface. For each comparison, we used equation (1) and (2) in Section 4.6.3 to calculate the distance.

$$LDIS_{i,j} = \Big(scanpath\big(YG1(i)\big), scanpath\big(YG1(j)\big)\Big) \qquad \textbf{(3)}$$

Second, after calculating the distances between all pairs of scan-paths on each interface among all participants of each age group, we calculated the average (mean) for nine interfaces of applications for each age group on each smartphone screen size, which is represented by MA as shown in equation (4):

$$MA_l = \left(\frac{1}{9}\right) * \left(\sum_{l}^{9}\left(\frac{1}{n} * \sum_{k=1}^{n} \mathrm{LDIS}_{i,j}(l,k)\right)\right) \qquad (4)$$

where *i* and *j* are the participants of an age group, *k* is the number of calculated distances for each application’s interface, and *l* is number of applications interfaces.

5.1.4 **Experimental Results and Discussions**

The average results and STD of the scan-paths dissimilarity for each age group are shown in Table 9, and the minimum and maximum average of scan-paths dissimilarity of two age groups on three smartphone screen sizes are shown in Figure 10 - Figure 12. Scan-paths dissimilarities for elderly users on small, medium, large screen sizes for EXP 1 are 10.37, 13.44, and 11.81 respectively; whilst for EXP 2 they are 6.93, 10.35, 10.44 respectively. The results show that scan-paths dissimilarities for elder are higher compared to the scan-paths dissimilarities associated with the younger users on small, medium, large screen sizes for both experiments (it is 4.41, 8.33, 7.33 respectively for EXP 1, and 3.00, 3.89, and 5.04 respectively for EXP 2). A high scan-path dissimilarity in browsing indicates that elderly users have difficulties in browsing smartphones applications compared to younger users. The scan-paths dissimilarity was high for elderly because their eyes visited most of smartphones applications contents before they could find a given target compared to younger users that their eyes visited few number contents to find a given target.

These results confirm our hypothesis H1 that scan-paths in browsing smartphone applications are age-driven. Our findings are in line with previous studies conducted on technology design in general (e.g. (Stößel, et al., 2010)), which found elderly have difficulties when interacting with technology. The elderly users' difficulties when browsing technology can be highlighted for the following reasons. First, as stated by (Victor, 2010), and (Fisk, et al., 2009), ageing is almost accompanied by a variety of changes represented by impairments in cognitive and motor movement abilities. Second, as concluded by (Stößel, et al., 2010), elderly people encounter difficulties when interacting with technology; this is because of technology devices are not designed to accommodate their special needs. Third, as stated by (Dyk, et al., 2013), and as shown in Table 8, and Figure 9-a, the elderly are less experienced with smartphone application use.

The average experience in using smartphones applications may have had an influence on the users' performance, which resulted high scan-paths dissimilarity for elderly users. Elderly users who took part in our research had a lower average experience in using the interfaces of smartphone applications at 0.18 years compared to younger users at 0.76 years.

Our research suggests that the elderly users have higher scan-paths dissimilarity which can be ascribed to the following reasons: 1) as stated by (Dyk, et al., 2013), and as shown in Figure 9-a, the elderly are less experienced in using the interfaces of smartphone applications; the shorter period of experience for elderly users in using smartphone applications (i.e. 0.18 years) compared to the longer experience of younger users (i.e. 0.76 years) has influenced in elderly users having a higher scan-path dissimilarity; 2) as reported by (Victor, 2010), (Fisk, et al., 2009), ageing is almost accompanied by a variety of changes represented by impairments in sensory perception of touch, cognitive and motor movement abilities, and 3) as stated by (Stößel, 2012) that technology design does not meet elderly users need – application interfaces are complex. It seems that all these factors can explain why the elderly have higher scan-paths dissimilarity on the interfaces of smartphones applications than younger users. Consequently, we suggest to avoid designing complex interfaces structures for the elderly.

Table 9. Average scan-paths dissimilarities for all age groups for three smartphone screen sizes.

Screen size	**Age group**	**EXP 1**		**EXP 2**	
		Mean	***(STD)***	***Mean***	***(STD)***
Small	YG 20-39	4.41	(3.31)	3.00	(0.85)
	EG 60+	10.37	(6.45)	6.93	(4.14)
Medium	YG 20-39	8.33	(4.30)	3.89	(1.90)
	EG 60+	13.44	(5.61)	10.35	(4.59)
Large	YG 20-39	7.33	(4.44)	5.04	(2.84)
	EG 60+	11.81	(3.61)	10.44	(2.19)

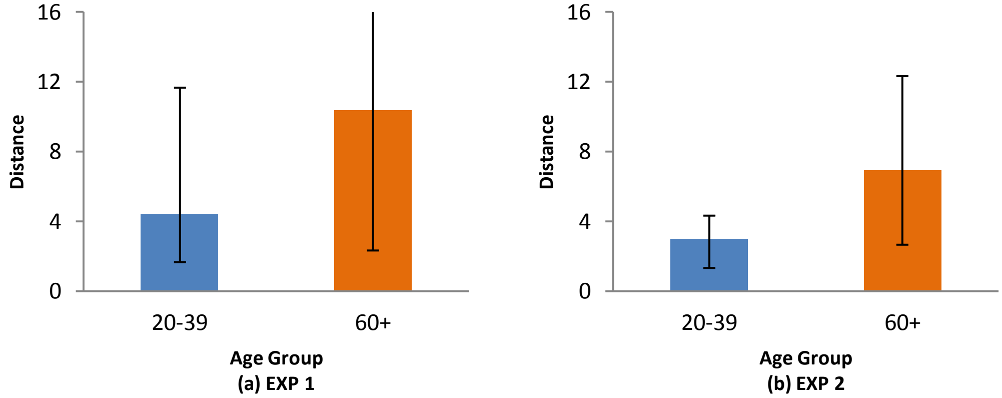


Figure 10. Minimum-Maximum mean distances for each group (high dissimilarity for elderly) on small smartphone: a) EXP 1, b) EXP 2.

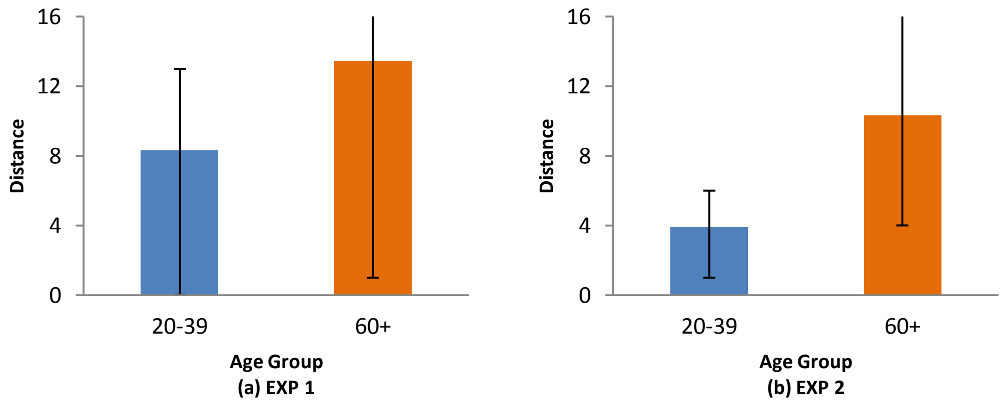


Figure 11. Minimum-Maximum mean distances for each group (high dissimilarity for elderly) on medium smartphone: a) EXP 1, b) EXP 2.

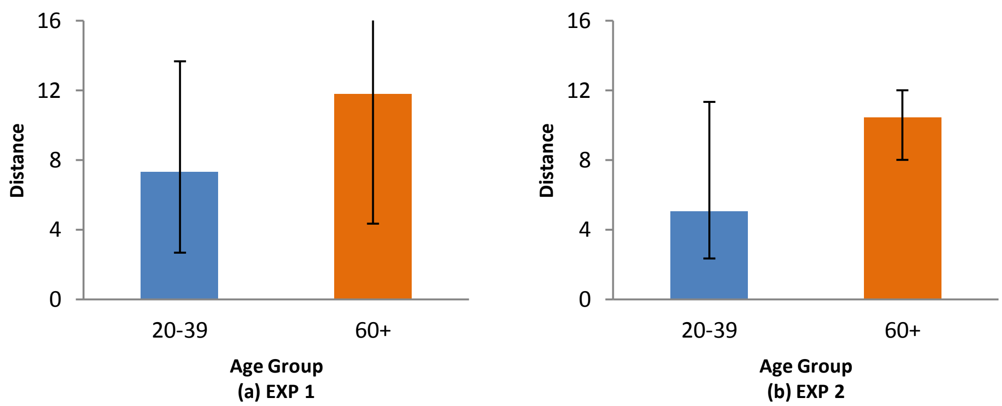


Figure 12. Minimum-Maximum mean distances for each group (high dissimilarity for elderly) on large smartphone: a) EXP 1, b) EXP 2.

Table 10. Average Scan-Path dissimilarities of 9 applications in EXP 1.

Screen size	App No	1	2	3	4	5	6	7	8	9
Small	YG	4.33	2	6	1.67	6.67	1.67	2	11.67	3.67
	EG	16.33	14.33	17.33	17.67	11.67	7.33	3.33	3	2.33
Medium	YG	10	13	11	10	8	13	0	5	5
	EG	13	19	18	17	10	15	1	17	11
Large	YG	2.67	13.67	13.00	4.67	12.33	4.33	3.00	7.00	5.33
	EG	11.33	14.00	15.00	16.33	12.33	8.33	4.33	12.33	12.33

Table 11. Average Scan-Path dissimilarities of 9 applications in EXP 2.

Screen size	App No	1	2	3	4	5	6	7	8	9
Small	YG	3.33	3	2.67	3.33	3.67	1.33	2.33	4.33	3
	EG	12.33	6.33	2.67	3	5	6.33	12.33	11.67	2.67
Medium	YG	6	3	2	3	6	1	3	6	5
	EG	6.5	12	4	4	10.33	14	11.33	16.67	14.33
Large	YG	11.33	3	2.33	2.67	4	6	5.33	7	3.67
	EG	14	8	10	8	11	9	12	13	9

The hypothesis H2 is designed to investigate if it is stimulus-driven or smartphone screen size-driven that has a greater influence on users' performance when browsing smartphones applications measured by scan-paths dissimilarity. In order to examine the hypothesis H2, we investigated the screen size-driven first as follows. The average scan-paths dissimilarity for elderly on medium screen size in EXP1 (13.44) is greater than the average scan-paths dissimilarity on both large and small screen sizes in EXP1 (11.81 and 10.37 respectively; see Table 9). Because of this, the first part of hypothesis H2 indicates that there was no influence of screen sizes on scan-paths dissimilarity of users.

In terms of the second part of hypothesis H2 – stimulus-driven, we considered each experiment (i.e. EXP 1, EXP 2) individually for the three smartphone screen sizes to investigate if the smartphone application is stimulus-driven. In other words, this investigates the influence of smartphone application's contents on users' performance measured by scan-paths dissimilarity when browsing smartphone applications. Based on the results in Table 10, and by taking the two smallest values of scan-paths dissimilarities of the nine interfaces of applications for each age group of each screen size, we will see App 7 is appeared 4 times out of 6 to be the larger number repeated in EXP 1 (see shading cells for App 7 in Table 10). Also, based on the results in Table 11 and by taking the two smallest values of scan-paths dissimilarities of the nine interfaces of applications for each age group of each screen size, we will see App 3 is appeared 4 times out of 6 to be the larger number repeated in EXP 2 (see shading cells for App 3 in Table 11).

User experience might have influenced users' performance to make the scan-path dissimilarity stimulus-driven than to be screen sizes driven for the users of two age groups. This could be explained by the following reasons. First, the participants' experience might have influenced their performance which made their scan-paths dissimilarity lower on some interfaces; the participants have longer experience in using the applications on PCs than their experience in using the same applications on smartphones shown in Figure 9. Note that the average experience in using the applications interfaces on *PCs* for EG is 5 years, and for YG is 4.15 years as shown in Figure 9. However, as shown in Figure 9-a, the average experience in using the applications interfaces on *smartphones* for EG is 0.18 years, and for YG is 0.76 years. So, using the applications on PCs might have influenced on the users performance when using the same applications on smartphones for having the same design and contents that will make the scan-paths dissimilarity lower on these interfaces. Secondly, it was found by (Al-Wabil, et al., 2008) and (Josephson & Holmes, 2002) that interfaces' stimulus have stronger effect when browsing the interfaces of web-pages on PCs. Their studies were conducted on a different population (i.e., dyslexic users with an average age of 31 years, and younger users with an average age of 22.5 years), and applications (i.e., website pages). It seems all these reasons may make the influence of stimulus more than the influence of screen sizes on users' performance.

Overall, the results showed that the scan-paths dissimilarity of browsing the interfaces of smartphone applications is tend to be influenced by stimulus than by smartphone screen sizes (i.e. a stronger influence by the stimulus than screen sizes). There was an influence for the stimulus in App 7 of EXP 1, and App 3 of EXP 2 - across all three smartphone screen sizes - that have lower scan-paths dissimilarities. However, there is no influence of smartphone screen sizes on the scan-paths dissimilarity on EXP 1. This proved the hypothesis H2 that scan-paths dissimilarity of smartphone applications are stimulus-driven than they are smartphone screen size-driven.

5.1.5 Section Conclusion

Based on examining pairs of scan-paths using Levenshtein algorithm, this research provided evidence of scan-path dissimilarities for the participants when browsing smartphones applications. The results showed evidence of ageing effect on performance (i.e., age-driven) that elderly users have high scan-paths dissimilarity than younger users when browsing smartphone applications. To the best of our knowledge, this is the first work to adopt age-driven in browsing smartphones applications using scan-paths on eye-tracking.

Furthermore, there was a lower dissimilarity of scan-paths for applications with popular contents such as active alarm application and account holder picture on the Skype application. These results suggest that viewing patterns on smartphone applications tend to be more stimulus-driven than to be smartphone screen size-driven. User experience might have influenced users' performance to make the scan-path age-driven and stimulus-driven as shown in Table 8, and Figure 9-a.

5.2. Difficulties in Local and Global Information Processing on Smartphones

In this section we will investigate the effects of user's age-group, as well as screen sizes on smartphone usability in terms of difficulties in information processing. The evaluation was performed using three different screen sizes of smartphones and tablets devices: small, medium, and large, and included three different age groups: elderly, middle-aged users, and younger users (see Sections 4.1 and 4.2 for more details on users and smartphones screen sizes respectively). An eye-tracker device was employed to obtain three metrics: fixation duration, scan-path duration, and saccades amplitude. All results have been statistically evaluated using ANOVA.

5.2.1 Overview of Experimental Hypotheses

The specific expectations that were examined in this experiment are hypotheses H3, and H4 regarding difficulties in information processing for users, and screen size influence on users' performance when browsing smartphones applications (see Section 4.4 for more details on the relevant hypotheses).

5.2.2 **Methodology**

Experiments Structure

Each of the three smartphone sizes (i.e., small, medium, and large) has two experiments: EXP1 and EXP2. Each experiment is conducted using participants from three age groups (i.e., EG, MG, and YG). As before, each participant was involved in only one smartphone screen size and in one experiment to avoid any influence of familiarity on the participant's performance. Figure 13 illustrates how experiments and different groups of participants are organized.

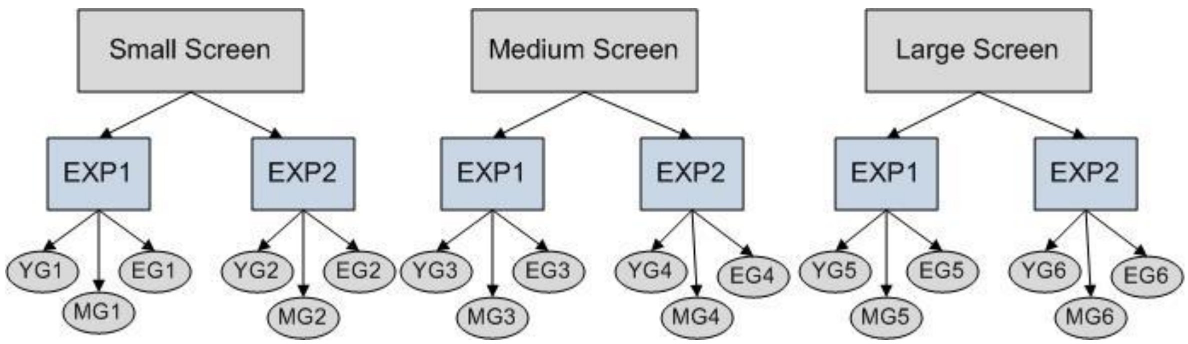


Figure 13. Organization of smartphone experiments and age groups.

Apparatuses

The smartphones of three screen sizes and the eye tracker device were used in this research to collect data. Specific details of the selected smartphones devices and eye tracker are available in Section 4.2 and in Section 4.7 respectively.

Participants and Stimuli

A total of 103 participants took part in the experiments as described in Table 12. The participants were selected from different age groups and include university students, university staff, and people from the local community. Each participant was asked to fill a demographic data form regarding age group, and their average experience in using applications; Skype, Facebook, and email, on smartphones/tablets and on PC (a data form is shown in Appendix-A). The explanation on how the average experience was calculated was described in Section 5.1.2 on *Participants and Stimuli*. The average experience on two age groups, and on two screen sizes of smartphones are shown in Table 12, and Figure 14. Figure 14-a shows the average experience of application use for two age groups on three smartphones screen sizes. Whilst Figure 14-b shows the average experience of application use for two age groups on PC. The nine interfaces of smartphone applications used as stimuli are explained in Section 4.5.

Table 12. Participant details.

Age Group	No. of participants	The average experience of applications use on smartphones/tablets
EG	22	0.36 years
MG	31	0.81 years
YG	50	1.73 years
Small smartphone	35	1.03 years
Mini-tablet	36	0.99 years
Large-tablet	32	0.89 years

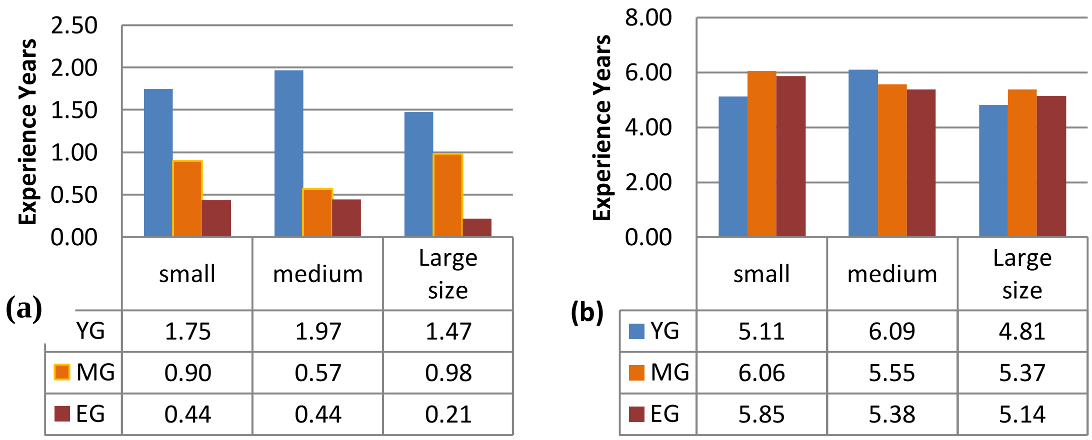


Figure 14. Average experience of applications use: a) on smartphones/tablets, b) on PCs.

5.2.3 **Experimental Design and Procedure**

The experiment design and procedure for this research was described in details in Section 4.7.

5.2.4 **Eye-tracking Metrics**

We used the following four eye-tracking metrics as dependent and independent variables to explore the determinants of visual browsing behaviour on smartphone interfaces. The dependent variables are: 1) FD, 2) SA, and 3) SPD. The independent variable is RS.

We calculated the average FD, RS, SPD and SA of each participant (based on non-erroneous search tasks of the nine search tasks) (Stößel, et al., 2010). A two-way ANOVA was used to provide the average, STD, and P-value for each age group. In ANOVA, we used $\alpha < 0.05$, which indicates the confidence level between the tested means.

5.2.5 Experimental Results and Discussions

The hypotheses H3 - H4 will be discussed in this research that elderly users have local and global information processing difficulties on smartphone applications compared to the middle-aged and younger users measured by FD and SPD respectively. Also, a small smartphone was difficult to use in browsing smartphone applications measured by RS. In Section 5.2.5 on *Do elderly users have both local and global information processing difficulties on smartphone/tablet use than other age groups?*, we will look at the information processing difficulties in local and global level using eye-movement tracking, and on *Do screen sizes have influenced on users interactions?*, we will look at the influence of smartphone screen sizes on the users' performance in terms of browsing smartphones applications using eye-movement tracking.

Do elderly users have both local and global information processing difficulties on smartphone/tablet use than other age groups?

Based on visual search behaviour using eye movement on smartphones applications, we investigated two kinds of information processing difficulties in local and global level measured by FD and SPD respectively. Fixation duration and scan-path durations results on small, medium and large screen sizes are shown in Table 13, Table 14, Figure 15, Figure 16, and Figure 17.

In terms of *information processing difficulties at local level*, the results show a significant ageing effect *($f= 20.213$, $p= 0.000$, $n^2= 0.25$)* measured by FD. Elderly users took significantly (i.e., p= 0.000) longer FD in 2922 milliseconds when compared to younger users who took 1686 milliseconds, and middle-aged (i.e., p = 0.019) who took 2376 milliseconds of FD. Also, the results show middle-aged took significantly (i.e. p = 0.000) larger than that of the younger-age group. The local information processing difficulties indicated that there are difficulties when interacting with interface contents, the elderly spend longer time (i.e., larger FD) in information processing on the interface contents, and this gives indication that some of application components on the interfaces were not properly designed for the elderly to be recognised promptly.

Table 13. Average and STD of FDs and SPDs across all three screen sizes for each age group when $P < 0.05$.

Age Group/	**YG**		**MG**		**EG**	
Metrics	**Mean**	**STD**	**mean**	**STD**	**mean**	**STD**
FD	1686 ↓	701.47	2376	857.84	2922 ↑	1267.19
SPD	1884 ↓	774.04	2810	973.34	3172 ↑	1428.21

Table 14. The average for all metrics: Fixation Durations, Scan-Path Durations. Arrow up shows larger value, and arrow down shows lower values.

Age Group	**Small Screen Size**				**Medium Screen Size**				**Large Screen Size**			
	FD		**SPD**		**FD**		**SPD**		**FD**		**SPD**	
	mean	**STD**	**mean**	**STD**	**mean**	**STD**	**mean**	**STD**	**mean**	**STD**	**mean**	**STD**
EG	2067 ↑	922	2152 ↑	1020	3615 ↑	1009	3401 ↑	1404	3397 ↑	1380	3812 ↑	1460
MG	1825 ↓	458	2325 ↓	768	2542 ↓	770	3142 ↓	937	2607 ↓	1096	2927 ↓	1097
YG	1467	701	1604	710	1891	569	2167	686	1738	777	1949	851

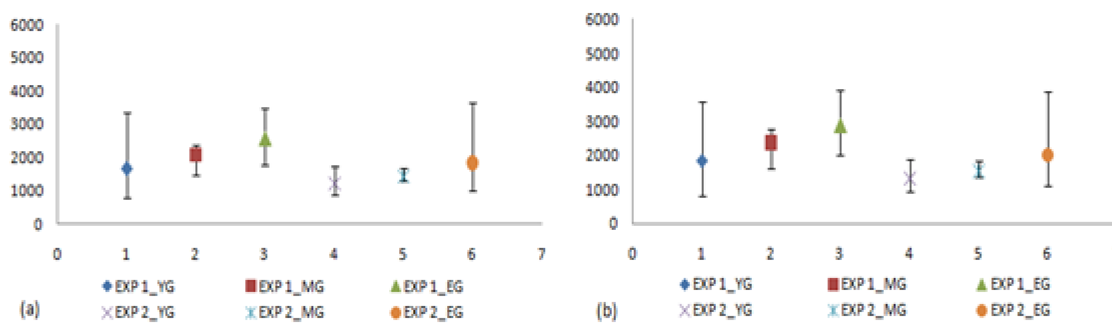


Figure 15. Eye-tracking metrics for small screen size. (a) Mean FD, and (b) Mean SPD, in millisecond.

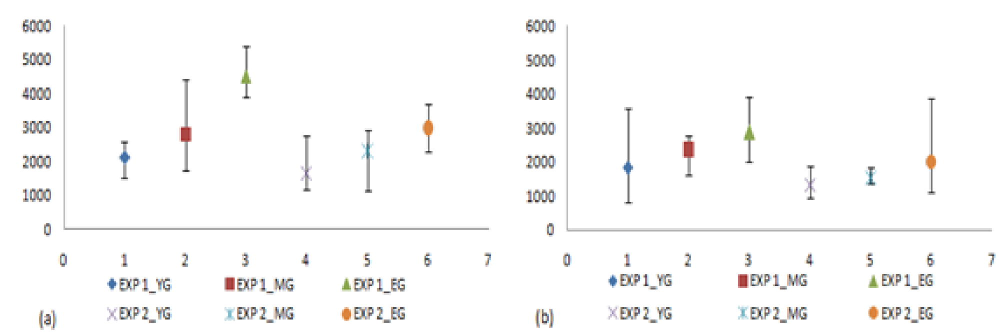


Figure 16. Eye-tracking metrics for medium screen size. (a) Mean FD, and (b) Mean SPD, in millisecond.

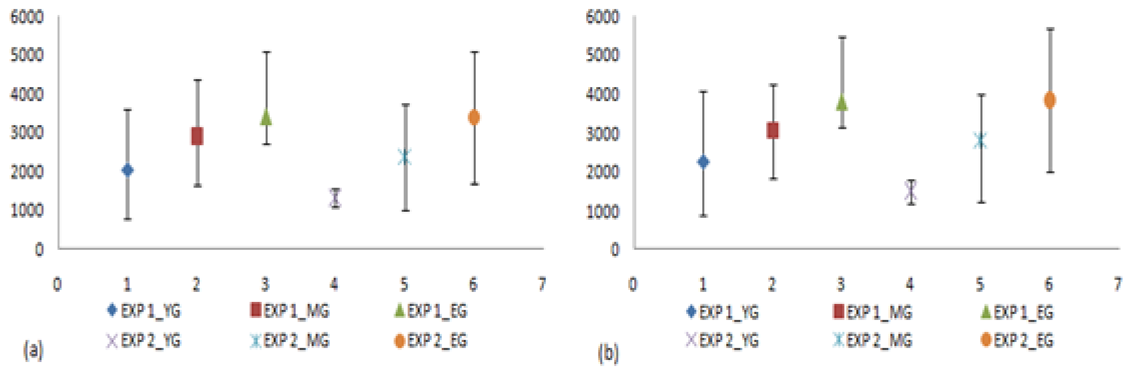


Figure 17. Eye-tracking metrics for large screen size. (a) Mean FD, and (b) Mean SPD, in millisecond.

In term of *information processing difficulties at global level*, the results show a significant ageing effect *(f= 15.667, p= 0.000, n^2= 0.21)* measured by SPD. Elderly users took significantly *(i.e. p = 0.000)* longer SPD in 3172 milliseconds when compared to younger users who took 1884 milliseconds, but not significantly *(i.e. p= 0.182)* between SPDs of elderly and middle-aged who took 2810 milliseconds. Also, the results show a significantly *(i.e. p= 0.000)* larger value of SPD for middle-aged and younger age group. The results provided evidence that the elderly have significant global information processing difficulties on smartphone applications measured by larger SPD. The results indicated that there are overall impediments in browsing the interfaces of applications, which might be related to the complex design of interface structures.

In addition, as shown in Table 12, and Figure 14-a, the average experience in using smartphones applications may have had an influence on the users' performance, which resulted in the difficulties at both local and global level information processing for elderly users. Elderly users who took part in our research had a lower average experience in smartphone applications use; Skype, Facebook, and email, at 0.36 years compared to middle-aged users at 0.81 years and younger users at 1.73 years. Whilst Figure 14-b shows the large average experience in using the applications on PC for elderly users, this large average experience on PC than on smartphone because some of elderly users used the email on PC for long time that reached to 20 years, but this large experience for elderly on PC compared to the middle-aged and younger users might not made influence on their performance in browsing smartphones.

These results support our hypothesis H3; elderly users exhibit difficulties in local and global information processing on smartphone applications represented by the larger values of FD and SPD respectively. Longer time-consuming searches can be caused by at least three factors as reported by (Chen, 2013), (Phiriyapokanon, 2011), (Wagner, et al., 2010) (Arnott, et al., 2004): 1) Inappropriate technology design (i.e., complex design). 2) Lack of user experience on the technology use. 3) Also, as it was mentioned in Chapter 2, impairments in users' ability can make the interaction difficult. For example, difficulties in remembering the steps to complete tasks.

Based on previous studies (e.g. (Chen, 2013), (Fukuda, 2008)) using different tools, condition, and applications it has been found that elderly users have difficulty when interacting with technology in general. It was concluded by number of studies (e.g. (Fukuda & Bubb, 2003), (Findlater, et al., 2013), (Froehlich, et al., 2007), Stößel, 2012)) that elderly users took longer time to perform a given task.

Do screen sizes have influenced on users interactions?

This question focuses on examining the influence of smartphone screen sizes on the users' performance in terms of browsing smartphones applications using eye-movement measured by ratio of saccades.

The average results of ratio of saccades (RSs) for the three smartphones screen sizes across three age groups are shown in Table 15, Figure 15, Figure 16, and Figure 17. The results show a significant influence of screen sizes on the performance efficiency of users across all age groups *(f= 4.467, p= 0.014, n^2= 0.04)* measured by RS. The average value of RS on large-tablet size is significantly *(i.e. p = 0.000)* larger in 1.584 than the average value of RS on mini-tablet that is 1.221, and significantly *(i.e., p = 0.000)* larger than on small smartphone that is 1.219. There is no significant difference between the RSs of small smartphone and mini-tablet *(i.e., p = 0.981)*. The efficient performance for all users was significantly better on large-tablet size for larger RS as mentioned above than mini-tablet, and small smartphone. Moreover, as shown in Table 12, and Figure 14, the average experience of participants in using smartphones applications who were involved in small smartphone is greater (1.03) than the experience for participants who were involved in mini-tablet (0.99), and who were involved in tablet large screen size (0.89), however, the large screen size still has larger ratio of saccades for the easy technology design that meet elderly users abilities. These results support our hypothesis H4, and in line with the study (Stößel, 2012)) that elderly users perform better when screen size is increased.

In addition, elderly users were more likely to suffer from age-related deficits when interacting with technology, which can act as an obstacle that makes technology use more difficult (Arnott, et al., 2004). The designers should consider the interaction difficulty with small screen sizes and the small interfaces contents in their designs for elderly users.

Table 15. Average ratio of saccades of three screen sizes. Significant differences for three screen sizes when ($p < 0.05$).

Metrics/Screen Sizes	Small		Medium		Large	
	Mean	**STD**	**Mean**	**STD**	**Mean**	**STD**
RS	1.219 ↓	0.303	1.221	0.395	1.584 ↑	0.669

5.2.6 Section Conclusion

In this research, we examined the local and global information processing difficulties, and screen sizes influence on smartphones usability. Experiments were conducted on three screen sizes involving participants of three different age groups. An eye-tracker was used to measure fixation durations, scan-path durations and saccades amplitude.

Impairments in motor ability, low cognitive ability, less experience of using smartphones, and a complex design can make the browsing on smartphone applications difficult for the elderly. The elderly exhibited more difficulties in information processing on smartphones at both local and global levels across all screen sizes than middle-aged and younger users. The results of ratio of saccades indicated that the usability in browsing smartphones applications on a large screen size is easy for all age groups compared to small smartphones, and mini-tablets.

In general, the results revealed a possible relationship between getting older with less experience in using smartphones and the complexity of interface design with smaller screen sizes of smartphones. Designers should consider the complex interface design for smartphone applications, and the difficult application structure that makes a global browsing difficult, specifically on small smartphones in their designs for elderly users.

5.3. Chapter Summary

This chapter presented two studies conducted on eye movement and smartphones for elderly users. First, the scan-paths dissimilarity using string-edit were examined on three screen sizes of smartphones involving two age groups; elderly users and younger users. The results showed evidence that there is ageing effect (i.e., age-driven) when browsing smartphones applications, where elderly users have higher scan-paths dissimilarity than the younger users. Furthermore, there was a lower dissimilarity (i.e., high similarity) of scan-paths for the applications with popular contents such as active alarm application (EXP1 - APP 7) and account holder picture on the Skype application (EXP2 - APP 3). These results suggest that viewing patterns tend to be more smartphone application stimulus-driven than to be smartphone screen size-driven. Second, an investigation on the information processing for users, and screen sizes influence on users' performance on smartphone/tablet use was conducted. The investigation was performed involving three age groups on three different screen sizes of smartphones and tablets devices. The results revealed that elderly exhibited more difficulties in information processing at both local and global level on smartphones across all screen sizes than did the middle-aged and younger users. The results of ratio of saccades indicated that the usability in browsing smartphones interfaces using eye-movement on a large tablet screen size is more usable for all age groups as compared to small screen sizes.

In general, the results revealed a possible relationship between getting older with less experience in using smartphones and the complexity of interface design with smaller screen sized smartphones for elderly users.

The following chapter presents two studies based on touch gestures to understand age-related usability issues of smartphones. Section 6.1 will address the research question Q2 for hypotheses H5 - H6 regarding the influence of ageing and screen sizes of smartphones in performing gesture swiping intuitively. Section 6.2 will address the research question Q3 for hypotheses H7 - H14 regarding the influence of ageing, screen sizes and gesture complexity in performing accurate gestures on smartphones.

CHAPTER 6

GESTURE-BASED APPLICATIONS ON SMARTPHONES FOR ELDERLY USERS

Previously in Chapter five, we showed results relevant to information processing difficulties for elderly users, and the stimulus effect on scan-path dissimilarities when browsing smartphone applications. This chapter presents two exploratory studies conducted using gesture-based applications on smartphones/tablets to address the research question Q2 described in Section 1.2, which is relevant to hypotheses H5-H6, and the research question Q3, also described in Section 1.2, which is relevant to hypotheses H7-H14. The first research was conducted to investigate the effects of ageing in performing gesture swiping intuitively. The second research was conducted to investigate the effects of ageing in performing gestures accurately, and to understand the influence of complex gestures on users' performance. The influence of screen size will also be considered in each of the two gesture studies. All results have been statistically analysed using ANOVA.

A particular interest of age in the two studies presented here is the elderly user group. Users of younger group were involved in these two studies in order to understand the difficulties faced by the elderly compared to users of other age groups. The outcomes of these studies will add to our understanding of the particular needs of elderly user population which will have implications for the effective technology design that meets elderly ability when executing gestures on touch-screen devices.

6.1. Gesture Swiping Interactions

Gesture swiping is one of the gesture movement patterns on touchscreens. The aim of this research is to examine the effect of ageing and screen sizes influence in performing gesture swiping intuitively on smartphones and tablets. A total of 35 participants from elderly and younger users were involved in the research to understand how users execute gesture swiping intuitively in four directions (i.e., swipe left, swipe right, swipe up, and swipe down), and to understand the influence of smartphone screen sizes on gesture swiping performed by users of two age groups.

We will show that the elderly users are less efficient, exert more force pressure, and they are less smooth in performing gesture swiping when compared to the younger users. Furthermore, elderly users are less efficient in swiping vertically, but not in swiping horizontally. Results show that a small smartphone is less usable for elderly users.

The rest of this section presents the experiment design and a detailed analysis of experimental results.

6.1.1 **Overview of Experimental Hypotheses**

The specific expectations that were examined in this experiment are hypotheses H5 and H6 which relates to the effect of ageing and screen sizes on users when performing gesture swiping intuitively (see Section 4.4 for more details on the relevant hypotheses).

6.1.2 **Methodology**

Experiments Structure

Our research is conducted on two sizes of smartphones and includes four gesture swiping directions (i.e. swipe left, swipe right, swipe up, and swipe down). Participants were divided into two age groups; EG, and YG. Each participant was involved in one only experiment to avoid any influence of familiarity on the participant's performance. Figure 18 below gives an overall view of the experiment setup.

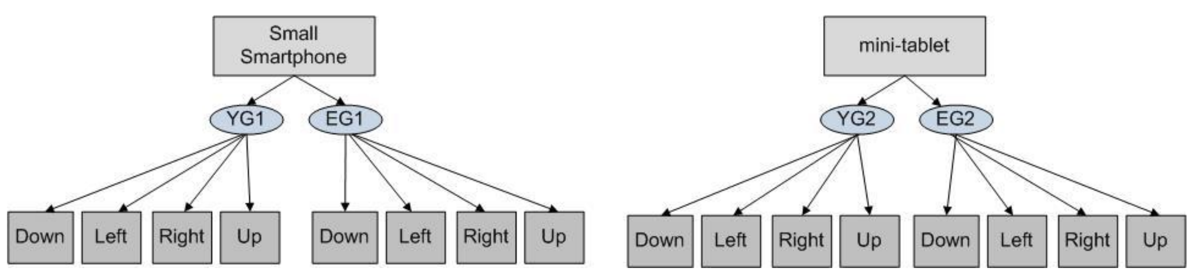


Figure 18. Organization of smartphone experiments and age groups.

Apparatus

Two sizes of smartphones were used in the research; small smartphone, and mini-tablet. Details of these devices were given in Section 4.2.

Participants

Details of the 35 participants who took part in the experiments are described in Table 16. The participants were selected from different age groups and include university students, university staff, and people from the local community. Each participant was asked to fill a demographic data form regarding their age group, and their average experience in using smartphones (a data form is shown in Appendix-B). The average experience of a participant was calculated based on their experience in using smartphones/tablets for calling and texting. For example, if a participant has 2 years of experience in using a smartphone for calling and texting on each of small smartphone, mini-tablet, and large-tablet size, the average experience of smartphones use for calling and texting on smartphones for this participant is 2 years. The participants' experiences of smartphone use for calling and texting were averaged based on the two age groups and the two screen sizes as shown in Table 16, and Figure 19.

Table 16. Participant details.

Age Group	No. of participants	No. of participants on small smartphone	No. of participants on mini-tablet	Average Age in years	The average experience for calling and texting on smartphones/tablets
EG	16	9	7	65.2	1.13 years
YG	19	8	11	25.4	0.96 years
Small smartphone	17	-	-	-	1.51 years
Mini-tablet	18	-	-	-	0.59 years

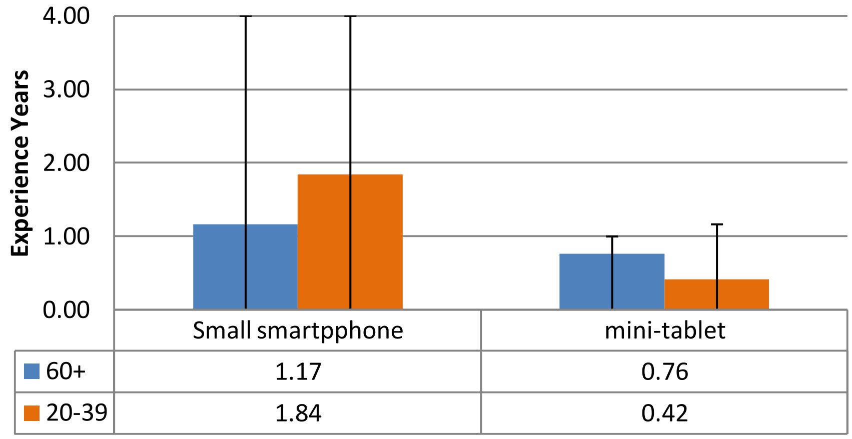


Figure 19. Average experience use for users on smartphones and tablets.

6.1.3 Experiment Design and Procedure

Experimental Design

Gesture swiping experiments included swiping in four directions (i.e., left, right, up, and down) and four targets (a target is a number in a list of numbers from 1 to 51) per direction. Participants were asked to swipe the smartphone/tablet touch-screen in one of the four directions at a time to find a given target number. Each swiping task starts from number '1' shown at the centre of the screen and ends when the participant taps on the target number. Figure 20 shows two example gesture swiping directions, each from start (i.e., number 1 shown in the first column) to target number (i.e., number 39 shown in the third column). The application was written in Java for Android Version 4.2.1, and the displayed numbers were designed using Photoshop.

The total number of tasks performed by a participant is 16 (i.e., 16 trials). Using 35 participants, we were able to collect a total of 560 trials of gesture swiping.

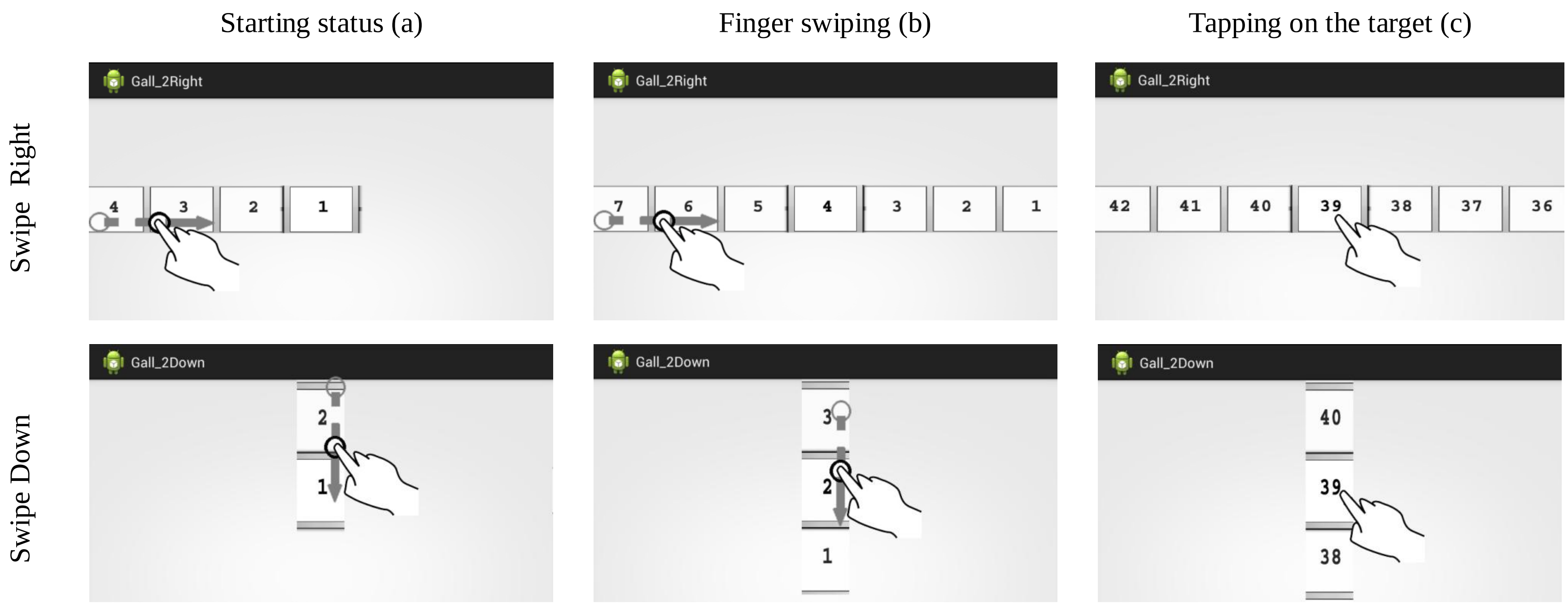


Figure 20. Gesture swiping tasks stages; a) a user start to swipe to right or to down, b) finger swiping to find a target (39), c) finger tap on the target (39).

Experimental Procedure

Each participant was invited to a computer lab in the university and was provided with a chair and table for the experiment. Each participant used a table with a comfortable distance and height that suits them. A description of the experiment was given to each participant; each participant was asked to practice one gesture (i.e. swiping down) for 2 times to familiarize themselves with the gesture tasks. The smartphone/tablet device was placed on a table in landscape orientation to ensure consistent experiment conditions for all the participants. The participant used one hand to hold the device on the table whilst using the other hand to perform gesture swiping tasks. This procedure was used to avoid any shaking of the smartphone/tablet that might occur if the users held the device in hand (physical ability among users vary). For example, finger pressure measurements could be influenced if the user pushes the screen from two opposite sides; downward pressure from the finger that performs gestures on the screen and upward pressure from the hand that holds the device. Note that Nicolau and Jorge (Nicolau & Jorge, 2012) used the landscape orientation in their study, but they let their participants hold the device in their hand (see description in Section 3.2.2 on *Gesture Accuracy and Gesture Complexity*).

Each of the four different gesture swiping directions (i.e., swipe down, swipe up, swipe left, and swipe right) was repeated four times for four different targets. The participants were asked to swipe images and hit (tap) the target (i.e., a given number). Once the participant hit (tap) the target number it moves to the centre of the screen which indicates the end of the gesture swiping task for that target number. The participants were asked to point to the target as quickly as possible. The targets for each direction (i.e., 39, 49, 44, and 35) were selected to be close to the last number on the list (i.e., 51) to let participants have enough distance to swipe on the screen. For each direction, the four numbers were selected randomly. Furthermore, the targets were selected to be different numbers to avoid any influence of familiarity on participant's performance in case if the participant received the same target number in more than one task.

6.1.4 **Dependent and Independent Variables**

Four metrics were used in this research to evaluate the effect of ageing and screen-size influence on gesture swiping interactions on smartphones. Three out of the four metrics will be considered to be the dependant variables: 1) MT (seconds), 2) FP, and 3) speed. The ratio of speed to FP metric is considered to be the independent variable (the metrics were explained in Section 4.9).

Each metric for a participant was calculated in three stages. First, for each participant, the metric for each target of each gesture direction was calculated (note that a number of swipes could be required to reach the target). Then we took the average of that metric obtained from the four targets (i.e., 39, 49, 44, and 35) of a specific direction as that participant's specific gesture task performance. Then we took the average of all four gesture directions (i.e., swipe down, swipe up, swipe left, and swipe right) of task performances as that participant's performance for a given metric. Finally, the average of all participants was taken based on the age-group and screen-size as necessary.

When calculating Gesture Speed, the Euclidean distance was used to calculate the distance between any two points on a trajectory of a gesture swipe.

6.1.5 Experimental Results and Discussions

The research hypotheses H5 and H6 regarding the effect of ageing and screen sizes on users when performing gesture swiping intuitively will be discussed in this section. Section 6.1.5 *on Does user age influence gesture swiping performance?*, will focus on the effects of ageing on gesture swiping performance, and on *Does smartphone screen size influence gesture swiping performance*?, will focus on the influence of smartphone screen sizes on the users' gesture swiping performance.

Does user age influence gesture swiping performance?

This question focuses on the effect of ageing in performing gesture swiping. Our findings revealed that elderly users have difficulty in performing gesture swiping compared to younger users. The average results of MT, FP, speed, and ratio of speed to FP for each age group across two screen sizes are shown in Table 17, Figure 21, and Figure 22.

In terms of the metric *movement time*, the results in Table 17 and Figure 21-a show that EG took significantly $(f = 14.646, P = 0.001, n^2 = 0.26)$ longer MT at 6.85 seconds than YG who took less MT at 5.05 seconds to complete gesture swiping tasks. Longer time spent on tasks indicates more difficulty in task performance. Our findings are in line with previous works in examining the effect of age on technology using MT where their results showed in general, elderly people took longer time to complete tasks using technology than younger people (Findlater, et al., 2013), (Farage, et al., 2012), (Stößel, et al., 2010), and (Rogers, et al., 2005).

Table 17. Average metrics for each age group across two screen sizes. Asterisks mark significant effects (* p< 0.05).

Features (metrics)	YG		EG		Sig.*
	Mean	STD	Mean	STD	
MT (seconds)	5.05 ↓	0.91	6.85 ↑	1.95	*
FP	0.25 ↓	0.12	0.31 ↑	0.12	
Speed	0.25 ↑	0.093	0.18 ↓	0.091	*
RSTFP	1.12 ↑	0.41	0.74 ↓	0.55	*
Vertically swiping (speed)	0.20 ↑	0.09	0.13 ↓	0.06	*
Horizontally swiping (speed)	0.31 ↑	0.11	0.25 ↓	0.14	

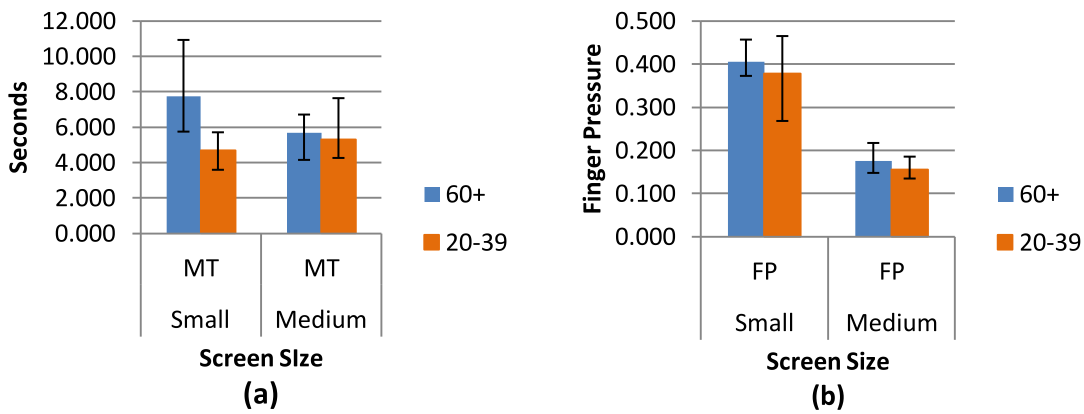


Figure 21. The average for (a) MT and (b) FP on screen sizes, and minimum and maximum averages for each age group.

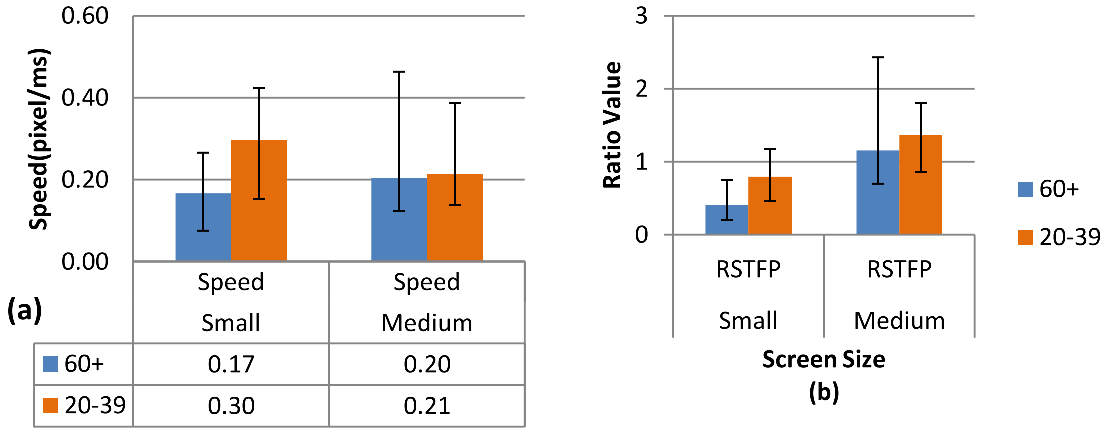


Figure 22. The average for (a) speed, and (b) RSTFP on screen sizes, and minimum and maximum averages for each age group.

Average *finger pressure* results of the gesture swiping research are shown in Table 17, and Figure 21-b. The results show that there were no significant effect on ages *(f = 2.994, p = 0.094, n^2= 0.01)* in exerting force pressure. However, the results show that, on average, elderly exerted more force pressure at 0.31 compared to younger users who exerted 0.25 force pressure. The study by (Moffatt & McGrenere, 2010) reported that elderly users exerted 50% more force pressure using pen-based interfaces on a tablet PC (laptop 12.1') than younger users. Our research suggests that the elderly users' problem in using technology is not with touchscreen, but can be ascribed to the following reasons: 1) as concluded by (Farage, et al., 2012), elderly users are known to use hard force pressure when interacting with technology (e.g. keyboard buttons); 2) as reported by (Victor, 2010), (Fisk, et al., 2009), ageing is almost accompanied by a variety of changes represented by impairments in sensory perception of touch, cognitive and motor movement abilities; and 3) as stated by (Dyk, et al., 2013), and as shown in Figure 19, the elderly are less experienced with smartphone application use. It seems that all these factors can explain why the elderly exerted more force pressure on smartphones than younger users. Consequently, we suggest considering this problem when designing touchscreen for the elderly, especially for gesture swiping to enhance the usability for elderly users because the response of technology does not meet elderly ability when executing gestures. This is to be equally efficient for elderly as it is for younger users.

Average *Gesture speed* results of the gesture swiping research are shown in Table 17, and Figure 22-a. The results show that elderly users were significantly *(f = 5.321, p= 0.028,*

n^2= 0.13) slower in performing gestures at a speed of 0.18 pixels/ms compared to the younger users at a speed of 0.25 pixels/ms. This indicates that elderly users were less efficient (i.e., slower) in performing gestures when compared to younger users. Our results are in line with previous studies (e.g. (Stößel, 2012), (Farage, et al., 2012), (Tu, 2012), and (Stößel, 2012)) that examined the effects of age on technology and concluded that the elderly are less efficient in performing tasks than younger users especially on small screen sizes.

In addition to the above observations, we noticed that the variance in the results for speed, movement time, and finger pressure between the users of two age groups comes from the performance difficulty when they are asked to hit (tap) the target as quickly as possible – it took more attempts for elderly users to correctly hit the target compared to younger users. The elderly users have difficulty in performing gesture swiping if the designers of smartphone touch screens do not consider accommodating elderly ability and expectations in terms of smartphone's response to user gestures.

Table 17, and Figure 22-b show results based on *ratio of speed to finger pressure,* which measures the smoothness of gesture performance. The ratio is derived to measure the relationship between performance efficiency measured by speed, and force pressure. The results show that, on average, elderly users have a significantly *(f= 5.862, p = 0.022, n^2= 0.09)* lower ratio at 0.74 than the younger at 1.12. Based on the above results, we conclude that elderly users were less smooth in performing gestures compared to younger users, indicating a difficulty faced by elderly.

Based on using speed of gesture swiping, we measured the performance efficiency of users for gestures in two orientations. First, in vertical gesture swiping (i.e., swipe up, swipe down), elderly users were significantly *(f = 9.089, p= 0.005, n^2= 0.19)* slower in task performance at a speed of 0.13 pixels/ms compared to the younger users at a speed of 0.20 pixels/ms. Second, in horizontal (i.e., swipe left, swipe right) gesture swiping, elderly were slower at a speed of 0.25 pixels/ms in task performance than younger users at a speed of 0.31 pixels/ms but not significantly *(f =2.059, p= 0.161, n^2=0.06)*. In other words, Elderly users were less efficient in performing vertical gesture swiping tasks compared to swiping gestures horizontally. This could be an indication that large display space (in landscape orientation) has a positive influence when performing gesture swiping tasks. Our finds are in line with previous studies (e.g. (Leitão, 2012)) that were conducted on elderly users based on task completion times, and number of attempts per task. Results by Leitão (Leitão, 2012) revealed that horizontal orientation gives the best performance for swiping tasks. We conducted our research systematically on gesture swiping in such a way that data were collected/measured in real-time by smartphone applications and this differs from the previous study by (Leitão, 2012) where they conducted their studies based on data collected (i.e., task completion times, and the number of attempts per task) by observing users as they performed the gesture tasks. Details of Leitão's work were explained earlier in Section 3.2.2 on *Gesture Accuracy and Gesture Complexity*.

The above results support our hypothesis H5; elderly users have greater difficulties in performing gesture swiping. To the best of our knowledge, we have not come across any study that has used finger-based touchscreens with gesture swiping to examine the effects of age on smartphones/tablets.

Does smartphone screen size influence gesture swiping performance?

This question focuses on the influence of smartphone screen sizes on the users' performance in terms of gesture swiping. The average results for FP, speed, and ratio of speed to FP for each screen size across two age groups are shown in Table 18, Figure 21, and Figure 22.

Average *finger pressure* results of the gesture swiping research are shown in Table 18, and Figure 21-b. The force pressure applied on small smartphones was significantly *(f = 264.430, p= 0.000, n^2 = 0.89)* higher at 0.39 force pressure compared to the mini-tablet at 0.16 force pressure when performing gesture swiping. The results reveal that the users of two age groups exerted more *force pressure* on small smartphones than on mini-tablets. As it was concluded by (Farage, et al., 2012) that the small interfaces' contents make the force pressure higher when the body makes full contact with the surface of the technology.

Gesture speed results of the gesture swiping research are shown in Table 18, and Figure 22-a. The results show that, on average, there were no significant influence of screen sizes on gesture speed *(f = 0.580, p=0.452, n^2= 0.02)* -- the average speed on the small smartphone is 0.23 pixels/ms compared to the average speed of 0.21 pixels/ms on the mini-tablet. The results show that the users' efficiency in performing gesture swiping was marginally better on the small smartphone compared to the mini-tablet. However, on closer inspection we found that it was the younger users who were much faster on the small smartphone (average speed of 0.30 pixels/ms on the small smartphone compared to average speed of 0.21 pixels/ms than on the mini-tablets) but the elderly users were slower on the small smartphone than they were on the mini tablet. We suspect that it is the user experience that might have contributed to the younger users' faster performance on the small smartphone – the average experience of younger users on small smartphones is 1.84 years compared to the average experience of younger users on mini-tablet, which is only 0.42 years (see Figure 19 for more details on user experience). Moreover, the elderly users' were more experienced on the small smartphone (i.e., 1.17 year) than the elderly users who were involved on mini-tablet (i.e., 0.76). However, the gesture swiping speed of elderly users on the mini-tablet is 0.20 pixels/ms, which is faster than the elderly users' gesture speed on the small smartphone (speed of 0.17 pixels/ms). See Figure 22 for more details. This indicates that the elderly users' performance has been affected by the screen size than by their experience (see Figure 19 for more details on users' experience).

Our results are in line with previous studies (e.g. (Stößel, 2012), (Farage, et al., 2012), (Tu, 2012), and (Stößel, 2012)) that examined the effects of age on technology and concluded that the elderly are less efficient than younger users in performing tasks especially on small screen sizes. Our findings substantiate the results of previous studies (e.g. (Stößel, 2012)) that showed large screen sizes can increase the performance of elderly users. Therefore we suggest designing touch interfaces with large displays to increase the usability of smartphones for the elderly (i.e., screen sizes, and interface contents).

Table 18. Average metrics for each screen size. Asterisks mark significant effects (*p< 0.05).

Features (metrics)	**Small**		**Mini-tablet**		**Sig.***
	Mean	**STD**	**Mean**	**STD**	
FP	0.39 ↑	0.05	0.16 ↓	0.03	*
Speed	0.23 ↑	0.11	0.21 ↓	0.09	
RSTFP	0.59 ↓	0.29	1.28 ↑	0.45	*
Vertically swiping (speed)	0.19 ↑	0.10	0.14 ↓	0.06	*
Horizontally swiping (speed)	0.28 ↓	0.13	0.29 ↑	0.13	

Table 18, and Figure 22-b show results based on *ratio of speed to finger pressure*. The results show that, on average, the value of ratio on the small smartphone was significantly *(f= 29.228, p= 0.000, n^2= 0.44)* lower at 0.59 than the ratio on the mini-tablet at 1.28 for users of two age groups. The performance on the mini-tablet was smoother compared to the ratio value on the small smartphone.

The gesture speed was used as a measure to examine the effects swiping orientation (*vertical and horizontal swiping orientation*) on gesture swiping. Results of gesture swiping speed for each of the two directions are given in Table 18. Across the two screen sizes, the users' of the two age groups were faster on horizontal swiping orientation. Regarding the influence of vertical swiping, the results show that, on average, the users of the two age groups were faster on the small smartphone *(f = 4.459, p=0.043, n^2= 0.09)* (average speed of 0.19 pixels/ms) than on the mini-tablet (average speed of 0.14 pixels/ms). The overall larger speed of vertical swiping orientation was a result of the younger users being much faster on small smartphone (average speed of 0.30 pixels/ms) than on mini-tablet (average speed of 0.21 pixels/ms). Whereas the elderly users were faster on mini-tablet (average speed of 0.20 pixels/ms) than on small smartphone (average speed of 0.17 pixels/ms). This was explained earlier under gesture speed paragraph. Stößel (Stößel, 2012) stated that increasing screen sizes increase the efficiency of users. This could explain the faster gesture swiping on horizontal direction compared to the slower gesture swiping in vertical direction.

The above results support our hypothesis H6; the screen size influences gesture swiping performance. Elderly users were less efficient in performing gesture swiping, exerted more force pressure, and were less smooth when swiping gestures on the small smartphone compared to their performance on the mini-tablet that have a larger screen.

6.1.6 **Section Conclusion**

Gesture swiping tasks were conducted to examine the effects of age on smartphone/mini-tablet, and to examine the influence of screen sizes on users of two age groups. The results showed that elderly users were less efficient in performing gesture swiping tasks, their swipes were less smooth in performing the task, and they exerted more force pressure to compensate for their impairment in sensory perception of touch, physiological impairments, and what we found to be their less experience in using smartphones, compared to the younger users.

In addition, the results show that the elderly were significantly less efficient in performing vertical gesture swiping, but not so in performing horizontal gesture swiping. Moreover, the small smartphone was less usable in terms of gesture swiping for elderly users. This is because small smartphones required more efficiency in swiping, more force pressure. Furthermore, swiping on small smartphones was not smooth for users.

Our findings indicated that getting older with lack of experience, and smaller screen sizes of smartphones, lead to difficulties in performing gesture swiping efficiently. We suggest that the designers consider elderly difficulties when swiping touch-gestures on smartphones in order to enhance the usability of smartphones and their applications for elderly users because the response of smartphones does not meet elderly ability when executing gestures.

6.2. Gesture Accuracy and Complexity

In Section 6.1 above, we investigated the effects of age and screen-size on smartphone usability based on gesture swiping performance *(swipe left, swipe right, swipe up, and swipe down)*. Now we will look at the effects of age and screen-size on smartphone usability based on gesture accuracy and complexity. A total of 50 participants from elderly and younger age groups were involved in this research that analysed their performance on eight gestures. The Dynamic Time Warping algorithm was used to measure gesture accuracy with respect to a reference gesture. The Euclidean distance was used to calculate gesture lengths to calculate gesture speed. Through experimental results, we will show that age and screen size influence the accurate execution of touch gestures on smartphones/tablets. We will show that elderly users are less accurate in performing touch gestures, they are less efficient, and they exert more force pressure - more so on small smartphones - when compared to the younger users. Also, we will show that complex gestures and non-complex gestures have influenced elderly users' performance, more so on small smartphones.

The rest of this section presents the details of experiment design and a discussion of results.

6.2.1 **Overview of Experimental Hypotheses**

The specific expectations that were examined in this experiment are hypotheses H7 – H14 which relate to the influence of ageing, screen size, and gesture complexity in performing gestures accurately. See Section 4.4 for more details on the relevant hypotheses.

6.2.2 **Methodology**

Experiments Structure

Our research was conducted on two sizes of smartphones and included eight gesture applications. Participants were divided into two age groups; EG, and YG. Figure 23 gives an overall view of the experiment setup. Each participant was involved only on one smartphone screen size to avoid any influence of familiarity on the participant's performance.

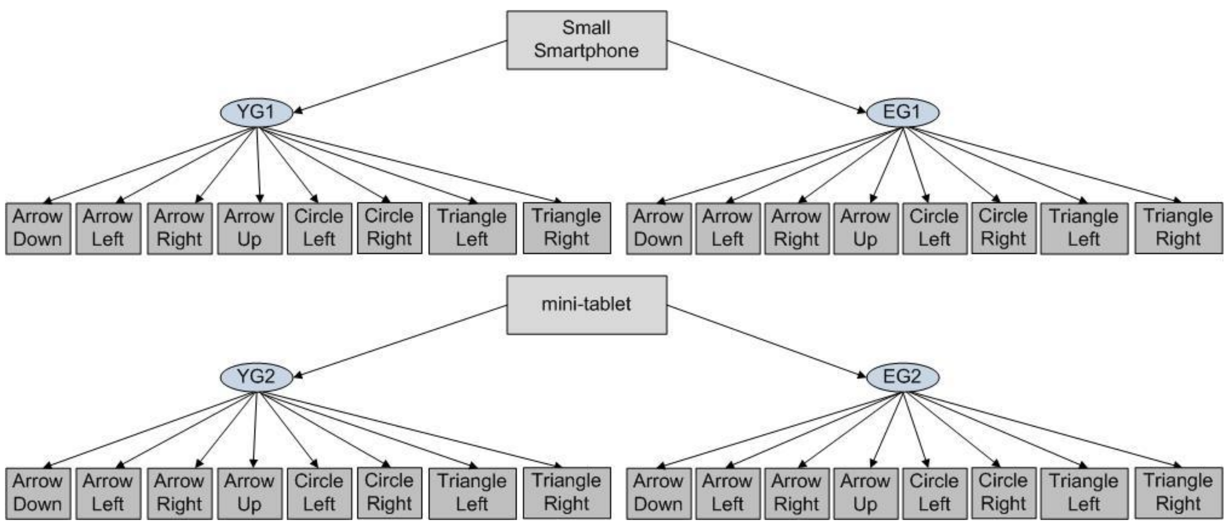


Figure 23. Organization of smartphone experiments, age groups, and 8 gesture applications.

Apparatuses and Gesture Applications

Two sizes of smartphones were used in the research; small smartphone, and mini-tablet. Details of these smartphones devices were given in Section 4.2. All eight gesture applications that we used in this research were explained in Section 4.8.

Participants

The participants were selected from different age groups and include university students, university staff, and people from the local community. Details of the 50 participants took part in the experiments are described in Table 19. Each participant was asked to fill a demographic data form regarding age group, and their average experience in using smartphones (a data form is shown in Appendix-B). The participants' experiences of smartphone use for calling and texting were averaged based on two age groups and two screen sizes and shown in Table 19 and Figure 24.

Table 19. Participant details.

Age Group	No. of participants	No. of participants on small smartphone	No. of participants on mini-tablet	Average Age in years	The average experience for calling and texting on smartphones/tablets
EG	25	13	12	64.77	0.67 years
YG	25	13	12	26.19	1.05 years
Small smartphone	26	-	-	-	0.77 years
Mini-tablet	24	-	-	-	0.95 years

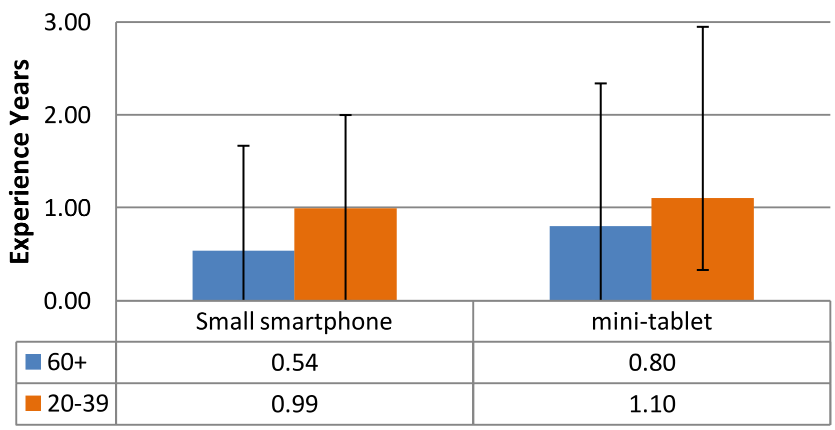


Figure 24. Average experience use for users on smartphones and tablets.

Table 20 shows the average participant finger base circumference in millimetres (mm) on each screen size. There were other measurements such as fingertip circumferences, finger length, and hand span, but since we could not collect these measurements from most participants we could not use them in the analysis (see Appendix, F - Table 36 for more details about the measurements and the data received). When examining the effect of *finger base circumference*, we excluded 9 out of 50 of the participants from the analysis because only 41 out of the 50 participants were measured using our scoring tools. The remaining 9 participants (i.e., P1, P9, P16, P25, P26, P30, P32, P39, and P47) sent us the measurements of their finger size via email, but we are not sure about the tools they used to score their finger size.

Table 20. Participant's finger base circumferences size.

Smartphone size	Age group	participant's finger base circumferences size ranged	Mean	Excluded participants due to unavailability of size data
Small smartphone	EG	50mm - 73.5mm	61mm	P1, P9, P16, P25, and P26
	YG	51.2mm - 65.3mm	59mm	
mini-tablet	EG	58.9mm - 73.5mm	66mm	P30, P32, P39, and P47
	YG	53.8mm - 73.5mm	61mm	

6.2.3 Experimental Design and Procedure

Experimental Design

Each participant repeated eight different gestures six times producing a total of 48 trials per participant. Therefore, the total number of trials collected from 50 participants is 2400. The Gesture Applications used in the research were illustrated earlier in Section 4.8

Experimental Procedure

This research includes eight gestures (i.e., circle to right, circle to left, triangle to right, triangle to left, arrow down, arrow left, arrow right, and arrow up) as shown in Figure 5, Section 4.8. Gesture data were collected by following the same procedure explained earlier in Section 6.1.3 on *Experimental Procedure*. Only the gestures and the number of repetitions were different; participants repeated each gesture six times. Participants were asked to trace gestures for each of the two circles and two triangles from the centre of the box (start point) through the middle of the path to the centre of the same box (start and the end points of the triangle and circle are represented by the same box) as shown in Figure 25 and Figure 26. With regard to the remaining four gestures (i.e., arrow down, arrow left, arrow right, and arrow up), the start and the end points of the gestures were represented by two boxes as shown in Figure 5, Section 4.7. In all gestures, an arrow was used as a guide to indicate the direction of the gesture. Following the instruction of (Teather, et al., 2010), the participants were asked to trace the complete gestures as quickly and accurately as possible.

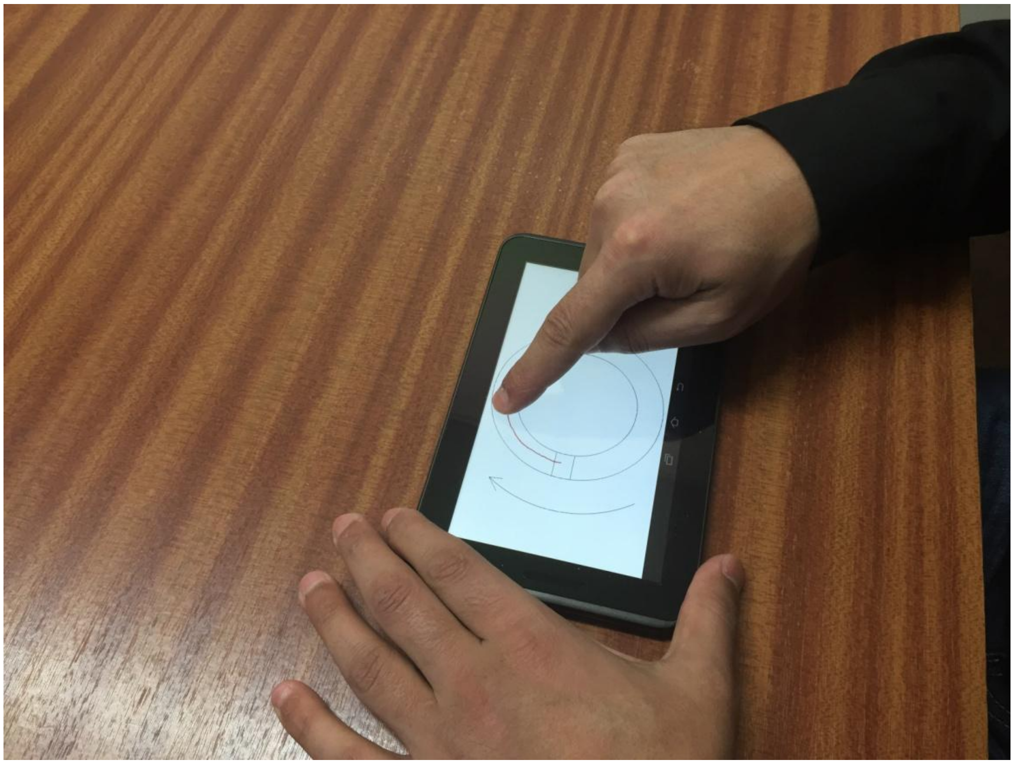


Figure 25. Capturing data for gesture accuracy experiments.

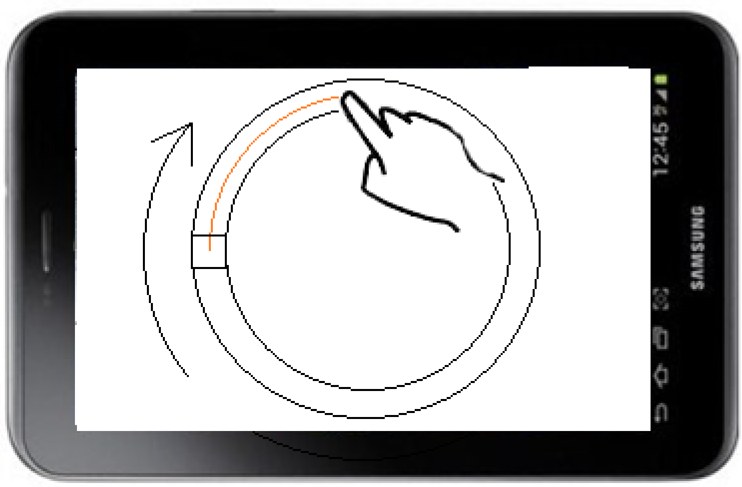


Figure 26. An illustration of the Circle to the Right gesture.

6.2.4 Dependent and Independent Variables

Five metrics were used in this experiment to evaluate the effects of ageing and screen size influence on users' ability to perform accurate gestures on smartphones. Four out of the five metrics will be considered to be the dependant variables: 1) MT (seconds), 2) FP, 3) gesture speed, and 4) gesture accuracy. The gesture complexity is considered to be the independent variable (the metrics were explained in Section 4.9).

The average metric for an age group or screen-size was calculated in three stages. First, we calculate the average metric (e.g. MT) of the six trials of a participant as the measurement of that participant's specific gesture task performance. We then took the average measurement of all eight gestures as that participant's performance for a metric (e.g. MT). Finally, the averages of all participants were taken based on the age-group and/or screen-size as necessary. Figure 7 in Section 4.9 showed how MT, FP, gesture speed, and gesture accuracy are calculated.

6.2.5 **Experimental Results and Discussions**

The research hypotheses H7 – H14 regarding ageing influence and screen sizes on users performing accurate gestures will be discussed here. Section 6.2.5 on *Does user-age and gesture-complexity influence the gesture accuracy?*, will focus on the effects of ageing on gesture accuracy, and on *Does the smartphone screen size influence gesture accuracy?*, will focus on the influence of smartphone screen size on gesture accuracy.

Does user-age and gesture-complexity influence the gesture accuracy?

This question focuses on the effect of ageing on gesture accuracy. The average results of gesture accuracy, MT, FP, and speed for each age group across two screen sizes are shown in Table 21, Figure 27, and Figure 28. To the best of our knowledge, this is the first research conducted on small smartphones and mini-tablets using touch-gestures for elderly users.

Movement time (MT) results show that on average, participants of the elderly group (EG) took significantly *($f = 23.321$, $P = 0.000$, $n^2 = 0.33$)* longer time (at 2.82 seconds) to execute the gesture tasks compared to participants of the younger group (YG) who took less time at (1.75 seconds) to complete the same gesture tasks. The longer time spent by elderly on the tasks indicates difficulty in gesture task performance compared to the younger users. Our findings are in line with previous works (Findlater, et al., 2013), (Farage, et al., 2012), and (Rogers, et al., 2005) on the effects of ageing on technology where their results showed, in general, elderly people taking longer time to complete tasks using technology.

Gesture speed results show that, on average, elderly users performed tasks at a significantly slower speed *(f=10.156, p = 0.003, n^2= 0.15)* (speed at 471.86 pixels/ms) compared to the younger users who completed the same tasks at a speed of 636.50 pixels/ms. As expected in hypothesis H7, elderly users were significantly less efficient (i.e., slower) in performing gestures than younger users. This is in line with previous studies that conducted on a large stationary touchscreen (e.g. (Stößel, 2012), (Stößel, et al., 2010)), where elderly users were found to be less efficient in performing tasks.

Table 21. Average metrics of gesture performance for each age group across two screen sizes. Asterisks mark significant effects (* P < 0.05).

Features (metrics)	YG		EG		Sig.*
	Mean	**STD**	**Mean**	**STD**	
Gesture accuracy	0.15 ↓	0.12	0.39 ↑	0.32	*
MT (seconds)	1.75 ↓	0.51	2.82 ↑	0.97	*
FP	0.28 ↓	0.11	0.33 ↑	0.13	*
Speed	636.50↑	174.73	471.86 ↓	206.09	*
Complex Gesture (speed)	587.63↑	137.42	571.50 ↓	381.77	
Complex Gesture (Gesture accuracy)	0.15 ↓	0.12	0.38 ↑	0.33	*
Non-complex Gesture (speed)	685.37↑	234.97	428.10↓	203.26	*
Non-complex Gesture (Gesture accuracy)	0.02 ↓	0.02	0.08 ↑	0.21	

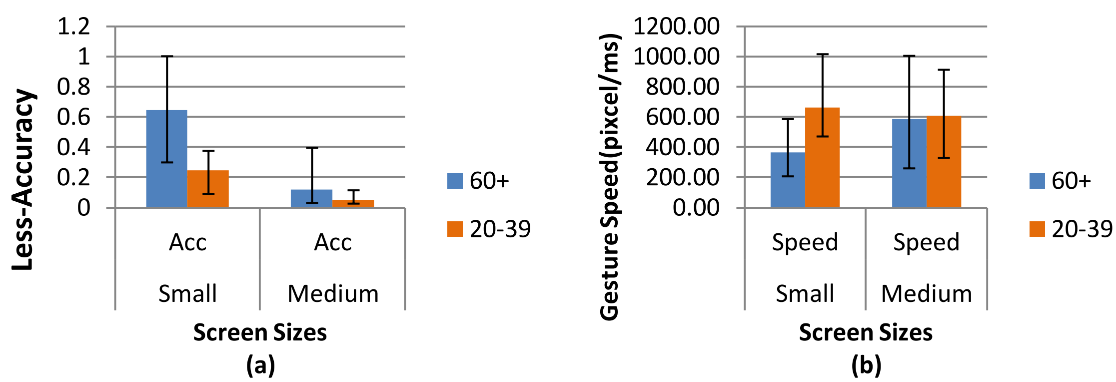


Figure 27. The average for (a) gesture accuracy, and (b) gesture speed on small smartphone and mini-tablet with a minimum and a maximum averages on each age group.

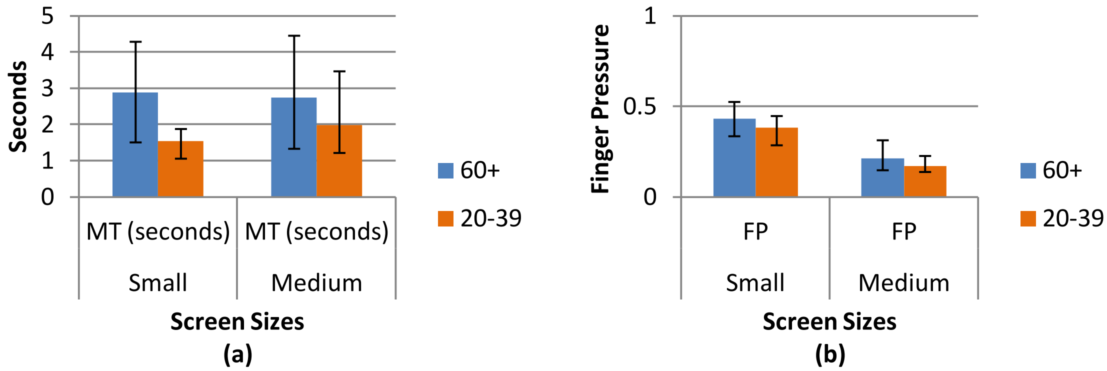


Figure 28. The average for (a) MT, and (b) FP on small smartphone and mini-tablet with a minimum and a maximum averages on each age group.

Gesture accuracy results are presented in Table 21, and Figure 27-a. Note that a larger distance between the optimal path of a gesture (i.e., reference data) and path obtained from a user indicates less accuracy in performing the gesture. Results show that, on average, elderly users are significantly less accurate in performing gestures *(f=36.392, p = 0.000, n^2= 0.20)* at gesture accuracy of 0.39 distance compared to younger users who performed gestures at an accuracy of 0.15 distance. This was as expected in hypothesis H8. Our results on the influence of age on executing gestures accurately are not in line with previous studies. For example Stößel, et al. (Stößel, et al., 2010) conducted a study for elderly on large touch-screens and found no influence of age on executing gestures accurately.

Our research is different to the work of Stößel, et al. (Stößel, et al., 2010) mentioned above in five main areas. First, we used widely available consumer devices in our experiments. Ours is the first research conducted on small smartphones using gestures for elderly users. This differentiates our research from previous studies that adapted large touchscreen devices to evaluate age effects on gestures by dividing the large touchscreen into different border sizes to compensate for the small touchscreen devices. Secondly, our experimental procedure was designed differently to the previous study; gesture path and the direction arrow of the required gesture remained displayed on the screen as a guide whilst the participant executed the gesture. This is different to the previous study where the gesture was displayed on the screen for a short period and removed prior to the participant executing the gesture. This procedure requires participants to remember the required gesture, its shape and its size; this could affect the performance due to memory load related factors, especially for elderly people. Thirdly, in our research, each participant was involved in performing the gesture experiment on only one screen size of smartphones. This was to avoid any influence on the participant's performance if they performed the gestures again on another device. This is different to the previous study where each participant performed the gestures on each of the three designed sizes of touchscreens. Fourthly, in our research, we have extracted the force pressure feature in our gesture analysis. This is different to the previous study which did not consider the force pressure for gesture analysis. Finally, we used DTW to calculate distances between the optimal path (i.e., reference data) of a gesture and the executed one (i.e., data obtained) considering all points along the trajectory of the gesture. This is different to the use of average angular deviation between a reference line and linear fit for the linear gestures. Whilst for the non-linear gestures (i.e. ellipse), optimizing the squared sum of orthogonal distances from the points and the fitted ellipse.

Based on speed and gesture accuracy results of elderly users discussed in the previous two paragraphs we noticed that the elderly users trade-off accuracy for speed (i.e., gesture speed is preferred over gesture accuracy). The ratio of gesture accuracy for elderly is large at 2.6% stance – based on the formula (i.e., EG gesture accuracy / YG gesture accuracy) compared to the ratio of speed for elderly at 0.74% (i.e., EG speed / YG speed) (see Table 21 for more details about the results). Therefore, gesture accuracy performance of elderly users is worse than their gesture performance speed.

Force pressure results show that, on average, participants of the elderly group (EG) exerted significantly more force pressure *(f= 11.229, p = 0.002, n^2= 0.04)* at 0.33 of force pressure compared to the participants of the younger group (YG) who exerted 0.28 of force pressure. This was as expected in hypothesis H9. Our research suggests that the elderly users' problem with using technology is multifaceted. One of the factors that might have contributed to the application of a greater force pressure on the smartphone touchscreens by elderly is their lack of experience using smartphone applications. On average, the elderly participants were less experienced on smartphone application use (i.e., 0.67 years) than the younger participants (i.e., 1.05 years) as shown in Figure 24. This needs further investigation and will be considered as part of our future work.

We investigated the influence of complex gestures on the users' gesture performance measured in terms of gesture speed and accuracy. In terms of *using speed to measure the* *influence of complex gestures* (i.e., circles and triangles), the results show that, on average, elderly users were slower (average speed of 571.50 pixels/ms) in performing complex gestures, but not significantly *($f=0.011$, $p = 0.916$, $n^2=0.00$)* compared to younger users who exhibited an average speed of 587.63 pixels/ms. Due to the large variations in performance among the participants, no age group effects were observed.

In terms of *the influence of complex gestures on gesture accuracy*, the results show that, on average, elderly performed complex gestures significantly *($f=35.844$, $p = 0.000$, $n^2=0.17$)* less accurately at 0.38 distance compared to younger users who performed complex gestures at 0.15 distance. This was as expected in hypothesis H10. Our findings are not in line with previous works such as (Stößel, et al., 2010) that their study showed that elderly little slower, but not necessarily less accurate than younger users across different levels of gesture complexity.

In addition to complex gestures, we investigated the influence of non-complex gestures (left, right, down, and up) on the users' performance using speed and gesture accuracy. In terms of using *speed* to measure the influence of non-complex gestures, the results show that, on average, elderly were significantly *($f=17.366$, $p = 0.000$, $n^2=0.26$)* slower (average speed of 428.12 pixels/ms) in performing non-complex gestures compared to younger users who exhibited an average speed of 685.37 pixels/ms. Whilst in terms of using *gesture accuracy* to measure the influence of non-complex gestures, the results show that, on average, elderly performed non-complex gestures less accurately but not significantly *($f=2.181$, $p = 0.147$, $n^2=0.04$)* (average gesture accuracy of 0.08 distance) compared to younger users who performed non-complex gestures at gesture accuracy of 0.02 distance. Elderly users were significantly less efficient when performing non-complex gestures.

In summary, the above results showed complex gestures significantly influencing elderly users' ability perform gestures accurately when compared to younger users. However, there were no significant differences in the speed of performing complex gestures by elder and younger users. The above results support our hypotheses H7-H10; elderly users have greater difficulties in performing gestures accurately. In general, elderly were slower, less efficient, less accurate in performing gestures, and they exerted more force pressure on the surfaces of touchscreens when compared to younger users. Also, complex gestures can significantly influence the elderly users' ability to perform gestures accurately.

We noticed that the result of gesture accuracy for all gestures (i.e. complex and non-complex gestures) for elderly users (average gesture accuracy 0.39 distance) is so close to the result when performing only complex gestures (average gesture accuracy 0.38 distance), as shown in Table 21. Whilst the participants performed the non-complex gesture very accurately (average gesture accuracy 0.08 distance). This showed that the influence of complex gestures on user performance was larger. These results reveal that elderly have large difficulty in performing complex gestures accurately compared with non-complex gestures.

Different users have different finger sizes which could influence gesture performance. We examined the influence of finger size (i.e., finger-base circumference) on user's performance based on three metrics (i.e., gesture accuracy, gesture speed, and finger pressure). We analysed gesture performance for all finger sizes across two screen sizes, and across two age groups for small fingers ranged (A to O), and large finger size ranged (W to Z+5). The results are shown Appendix, F: Table 37, Table 38, and Table 39. The average of gesture accuracy for small and large finger size was (0.36 and 0.23 respectively. The average finger pressure for small finger size was 0.32, while it was 0.29 for large finger size. The average speed for small finger size was 547, while it was 555 for large finger size.

In conclusion, we found a potential relationship between finger size and user performance on based on finger-based circumference. However, our analysis was conducted on a small sample of participants and the results did not show any significant differences for finger pressure and speed. We suggest conducting further investigations using a large number of participants for each range of finger sizes and measurements that we suggested in the Appendix, F.

Does the smartphone screen size influence gesture accuracy?

This section examines the influence of smartphone screen size on the users' performance in terms of gesture accuracy. The average results of gesture accuracy, FP, speed, and gesture complexity for each screen size of smartphones across two age groups are shown in Table 22, Figure 27, and Figure 28. More detailed results for each age group on each screen size of smartphones are shown in Table 23.

The *gesture speed* results reveal that, on average, the users of two age groups performed tasks at a slower speed, but not significantly *($f= 2.689$, $p = 0.108$, $n^2= 0.04$)*, (average speed of 514.88 pixels/ms) on the small smartphone compared to the users of two age groups who completed tasks on mini-tablet at an average speed of 596.76 pixels/ms. The results show that the users' efficiency in performing gesture speed was marginally better on the mini-tablet (i.e., larger value of speed) compared to the small smartphone. This was as expected in hypothesis H12. This finding supports Stößel's study (Stößel, 2012) conducted on gestures for elderly users where they found elderly users' performance efficiency to increase when increasing the screen size.

G*esture accuracy* results reveal that, on average, the users of the two age groups are significantly less accurate (gesture accuracy of 0.45 distance) in performing gestures on the small smartphone *($f=85.613$, $p = 0.000$, $n^2= 0.46$)* compared to the users who completed tasks on the mini-tablet with a gesture accuracy of 0.08 distance. This was as expected in hypothesis H13. The results suggest that practical performance of gestures by users increased when screen size increased. This is in line with the study by Stößel (Stößel, 2012) in that they reported screen size influences the users' ability to perform gesture accurately.

Force pressure results show that, on average, the users of both age groups exerted significantly *($f= 240.139$, $p = 0.000$, $n^2= 0.81$)* more force pressure on small smartphone at 0.41 of force pressure compared to the users who completed the gesture tasks on the mini-tablet at 0.19 of force pressure. This was as expected in hypothesis H14. The user's performance on small smartphone required large force pressure than on mini-tablet.

In terms of using *gesture speed* to measure the influence of screen size with gesture complexity on user's performance, the results in Table 22 show that, on average, the users were significantly *($f=5.904$, $p= 0.019$, $n^2=0.10$)* slower in performing complex gestures on the small smartphone (average speed of 495.23 pixels/ms) compared to the users who completed the tasks on the mini-tablet (average speed of 670.93 pixels/ms). This indicates that the efficiency in performing complex gestures on a mini-tablet across the two age groups was better (i.e., faster) than on a small smartphone.

Table 22. Average metrics for each screen size across two age groups. Asterisks mark significant effects (* p < 0.05).

Features (metrics)	**Small**		**mini-tablet**		**Sig.***
	Mean	**STD**	**Mean**	**STD**	
Gesture accuracy	0.45 ↑	0.27	0.08 ↓	0.088	*
FP	0.41 ↑	0.06	0.19 ↓	0.04	*
Speed	514.88↓	210.13	596.76 ↑	198.18	
Complex Gesture (speed)	495.23↓	163.33	670.93 ↑	355.23	*
Complex Gesture (Gesture accuracy)	0.44 ↑	0.26	0.07 ↓	0.06	*
Non-complex Gesture (speed)	534.53↓	266.94	580.78↑	241.01	
Non-complex Gesture (Gesture accuracy)	0.03 ↓	0.09	0.07 ↑	0.20	

Table 23. The average gesture accuracy results for users and screen sizes together.

Screen Sizes	**Features**	**Age Group**	**EG**	**YG**
Small smartphone	Gesture accuracy	Mean	0.65 ↑	0.25 ↑
		STD	0.23	0.08
	Speed	Mean	366.40 ↓	663.36 ↓
		STD	120.00	172.68
	FP	Mean	0.43 ↑	0.38 ↑
		STD	0.07	0.05
mini-tablet	Gesture accuracy	Mean	0.12 ↓	0.05 ↓
		STD	0.11	0.03
	Speed	Mean	586.12 ↑	607.40 ↑
		STD	222.64	179.74
	FP	Mean	0.21 ↓	0.16 ↓
		STD	0.05	0.02

In terms of using *gesture accuracy* to measure the influence of screen size and gesture complexity on user's performance, the results in Table 22 show that, on average, the users of the two age groups performed complex gestures significantly *(f= 102.418, p = 0.000, n^2=0.49)* less accurately on the small smartphone (gesture accuracy of 0.44 distance) compared to the users of the two age groups who completed the tasks on the mini-tablet (gesture accuracy of 0.07 distance). This means performing complex gestures on the mini-tablet was more accurate than on the small smartphone. Our findings are in line with Stößel, et al. (Stößel, et al., 2010) where they found gesture complexity and screen sizes to have influenced users' performance in terms of velocity and form stability. To conclude, based on gesture accuracy and gesture speed, we found a significant influence of complex gestures and screen sizes on users' performance. This was as expected in hypothesis H11.

In terms of using *gesture speed* to measure the influence of screen sizes with non-complex gestures on user's performance, the results reveal that, on average, the users of two age groups were slower in performing non-complex gestures on small smartphone, but not significantly *($f= 0.583$, $p = 0.449$, $n^2=0.01$)* (average speed of 534.53 pixels/ms) compared to performance on mini-tablet (average speed of 580.78 pixels/ms). Whilst in terms of using *gesture accuracy* to measure the influence of screen sizes on non-complex gestures, the results show that, on average, the users of two age groups performed non-complex gestures less accurately on mini-tablet but not significantly *($f=0.567$, $p= 0.455$, $n^2=0.01$)* (gesture accuracy of 0.07 distance) compared to the performance on small smartphone (gesture accuracy of 0.03 distance). The results for non-complex gestures using gesture accuracy were better on small smartphones. The users perform non-complex gestures accurately because the non-complex does not have curves or corners.

In summary, the results revealed that the users were *significantly* less efficient and less accurate when performing complex gestures on small smartphone. We found a relationship between getting older, decreasing screen size, complex gestures, gesture accuracy and performance efficiency, and force pressure. The above results support our hypotheses H11 - H14; a small smartphone was difficult for users to perform gesture accurately. The users of the two age groups were less efficient and less accurate when performing complex gestures on small smartphones.

6.2.6 **Section Conclusion**

This research provides new insight into how accurately and efficiently elderly users can execute gestures specifically on small smartphones and mini-tablets devices. The metrics used to analyse the effects of age and screen-size on gesture performance were MT, FP, gesture speed, and gesture accuracy. Dynamic Time Warping was used to measure gesture accuracy; the Euclidean distance was employed to calculate gesture lengths when calculating gesture speed.

The results showed that there was a systematic influence of ageing and screen sizes on performing gestures accurately. Elderly users were significantly less accurate when performing gestures - worse on the small smartphone. Furthermore, elderly users were less efficient, and they exerted more force pressure compared to the younger users. Also, the users, the elderly in particular, were less efficient and less accurate when performing complex gestures on the small smartphone compared to the mini-tablet. In addition, we found a potential relationship between finger size and user performance. This needs further investigation and will be considered as part of our future work.

Results indicated that there were relationships between old age, low accuracy and efficiency in gesture performance, complex gestures, and smaller screen size of smartphones. This needs to be considered for future universal design of smartphone/tablets as the usability of smartphones for elderly users is not the same as it is for younger users. The feedback received for touch-gestures does not meet elderly ability when executing gestures.

6.3. Chapter Summary

This chapter conducted two studies using touch-gestures on smartphones and mini-tablets. The first research investigated the effects of age and screen sizes on performing gesture swiping intuitively on smartphones and tablets. A total of 35 participants from elderly and younger age groups were involved to understand how users perform gesture swiping intuitively in four directions. Also, smartphones of two screens sizes were used to examine the influence of smartphone screen size on users of two age groups. The results showed that elderly users were less efficient in performing gesture swiping tasks, their gesture swipes were less smooth, and they exerted more force pressure than younger users. In addition, the elderly were significantly less efficient in performing vertical gesture swiping, but not so when performing horizontal gesture swiping. Moreover, the small smartphone was less usable for users of both age groups, more so for elderly.

The second research investigated the relationships among gesture accuracy, gesture complexity, user age, and screen-size. A total of 50 participants from the elderly and the younger age groups were involved in the research that analysed user performance on eight gestures. Dynamic Time Warping was used to measure gesture accuracy and the Euclidean distance was used to calculate gesture lengths to calculate gesture speed. The results showed that there were age and screen size influences on gesture accuracy. Elderly users were less accurate in performing gestures - worse on the small smartphone. Furthermore, they were less efficient, and they exerted more force pressure. The users, the elderly in particular, were significantly less efficient and less accurate in performing complex gestures on the small smartphone compared to the mini-tablet.

The above results indicate the possibility of using gesture based metrics such as movement-time, finger-pressure, gesture speed, and gesture accuracy as discriminant features to classify a user’s age-group. Motivated by this observation, the next chapter will investigate the possibility of classifying a user’s age-group based on his/her ability to perform touch-gestures on smartphones.

CHAPTER 7

USER AGE-GROUP CLASSIFICATION USING GESTURE-BASED FEATURES

This chapter investigates the possibility of classifying users' age-group using gesture-based features on smartphones and aims to address the research question Q4 described in Section 1.2, which is relevant to hypotheses H15 and H16. The work presented here was motivated by the results in Section 6.2 of the previous chapter where we found significant differences in touch-gesture performance by elderly compared to younger users. For example, elderly users were slower and less accurate in performing gestures compared to younger users. Furthermore, elderly users exerted more pressure on the touch-screen than their younger counterparts. Based on these observations, we propose the use of four touch-gesture based metrics, i.e., *gesture accuracy, gesture speed, finger pressure,* and *movement time,* as discriminant features to classify to users' age-group. This is also to investigate the usefulness of gesture-based features on classifying users' age-groups.

We considered different scenarios of application where in one scenario we assumed to have prior knowledge of individual user behaviour (i.e., user-dependent age-group classification) and in others we assumed to have no knowledge of individual user behaviour (i.e., user-independent age-group classification) as shown in Figure 29. On each scenario, two kinds analysis were considered; single feature and combination between features. Also, the influence of screen size on age-group classification accuracy was considered in this research.

In this chapter, we will demonstrate the possibility of classifying user's age-group using touch-gesture based features for both user-dependent and user-independent scenarios. A higher classification accuracy can be achieved on small smartphones compared to mini-tablets. This could be because users of all age groups experienced similar difficulties when interacting with small-size smartphones resulting in both age groups producing similar gesture-based features/measurements. We will also show that the classification accuracy is relatively higher for the younger age group compared to the elderly age group; this is because some elderly users were able to perform touch-gestures with similar characteristics to the younger age group.

The outcomes of this particular research could be used as a system to adapt itself to let users interact with technology based on their age-related abilities, i.e., the system will turn into a particular setting based on its current user's age-group (note that different interface designs were highlighted and discussed in Section 2.2.3). This could be particularly helpful to users who are unable to setup their own smartphone, tablet or a similar device to their own preferences or for public systems that could be used by different users at different times.

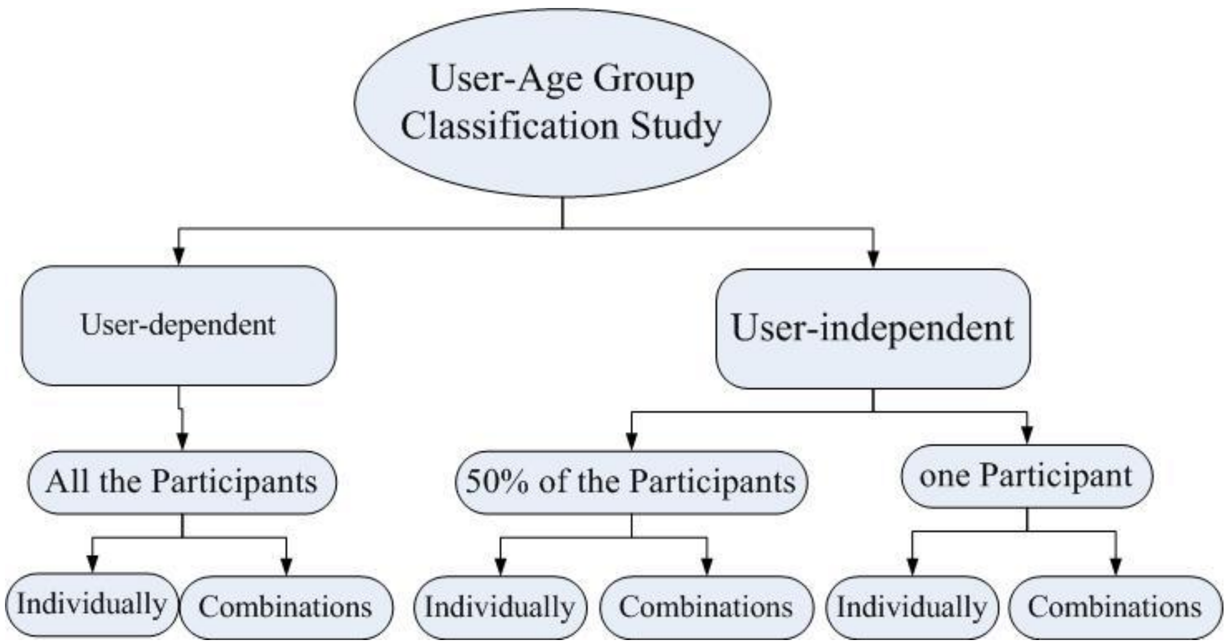


Figure 29. Organization of Users age-groups classification research.

7.1. Overview of Experimental Hypotheses

The specific expectations that will be examined in this research are hypotheses H15 and H16 that relate to the possibility of classifying a user's age-group and the influence of screen size on the classification accuracy (see Section 4.4 for more details of the relevant hypotheses).

7.2. Methodology and Data Collection

The apparatuses, gesture applications, and participants were explained earlier in Section 6.2.2. Participants' gesture-based data were collected earlier in Chapter 6. In summary, the user age-group classification included 50 participants (25 Elderly and 25 younger) as shown in Section 6.2.2 on *Participants* and the eight gestures as shown in Figure 5. The participants performed each gesture six times (six trials). Therefore, the total number of gesture samples acquired were 2400 which reached to 9600 trials when we extracted the four features from each gesture sample. The four features were extracted from the previous research in Section 6.2.2 to be used in the users' age-groups classification research. More details about these features and the process we followed to classify users' age-groups are presented in the next sections.

7.3. Touch-gesture based Age-related Features

The set of touch-gesture based features used here for age-group classification are the four metrics, i.e., gesture accuracy, gesture speed, finger pressure, and movement time we used in the previous chapter. These four metrics were introduced earlier in Chapter 6, Section 6.2.4.

7.4. User Age-Group Classification Process

The classification process includes a training stage and a testing stage. The training stage is used to represent an age-group (on all screens or for a specific screen size) by preparing feature vectors for individual metrics, and depending on the experiment, a combined feature vector. The first of the six samples (trials) of a gesture was used for training. During testing, a feature vector representing a user will be compared with the two training feature vectors (one per age group) using Euclidean distance. The user's age-group will be classified based on the nearest neighbour (NN), since there are only two exemplars in the training dataset. Testing was performed by using the five samples of the gesture data that were not part of the training data.

The training data (i.e., the feature vectors representing the younger age-group and the elderly age-group) are calculated as follows. Calculate the average metric M_i (e.g. gesture speed) of an age group (e.g. younger age-group) for a specific gesture G_j (e.g. Circle-left) on a specific screen-size (e.g. small) by using the first sample of that gesture performed by each participant from that age-group. Likewise, calculate the average metric M_i for the seven remaining gestures for the same screen-size and age group. This gives the feature vector for metric M_i which consists of eight coefficients that represents an age group in the training data set. Figure 30 shows an example of how we extracted the training dataset and the testing dataset for one age group (e.g. elderly users) on the small smartphone using only one metric (e.g. MT). The feature vectors for the other three metrics are calculated the same way. We will look at the classification accuracy of individual metrics as well as combinations of them – concatenate feature vectors of individual metrics to produce a combined (i.e., fused) feature vector of 32 coefficients.

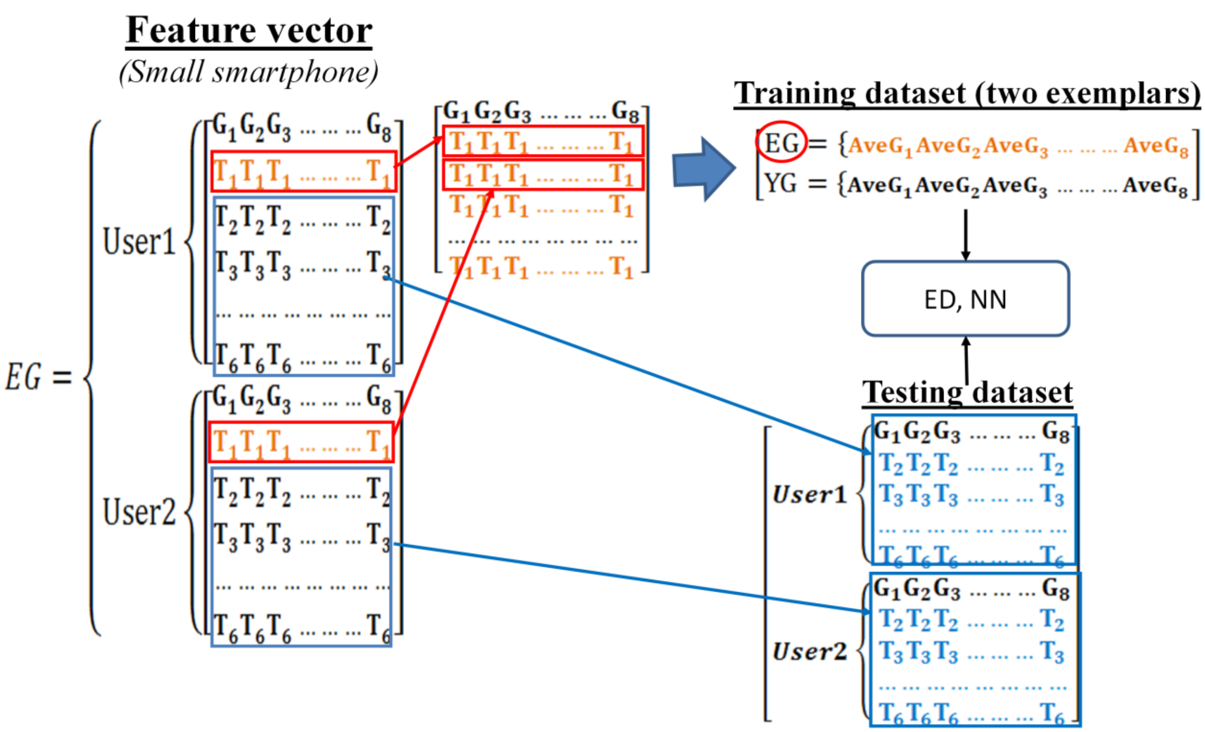


Figure 30. User age-group classification process.

We found some similar work in (Hurst, et al., 2008) to our research in users age-groups classification research. However, our research is different to Hurst et al. in three main areas. First, they based their measurement on PC mouse movements, but we used finger-based touch-gestures on smartphones. Second, their study used the following metrics: 1) the movement time needed to complete the task, and 2) the number attempts needed to perform a task correctly. Whereas the metrics used in our research are: gesture accuracy, gesture speed, finger pressure, and movement time. Also, we used dynamic time warping (DTW), and Euclidean distance (ED) to calculate gesture accuracy, and gesture lengths to calculate speed respectively (see Section 6.2 for more details about how gesture accuracy and gesture speed were calculated). Finally, Hurst et al. used decision trees based on the *observation* in the statistical analysis, whereas in our research, we used nearest-neighbour (NN) with ED to classify user's age-group.

7.5. Experimental Results and Discussions

In our research, the effect of age and screen size influence were considered for three scenarios: user-dependent (100%); user-independent with 50% training data; and user-independent with data from one participant per age-group as training data. The explanation given in the previous section was for training data relevant to user-dependent scenario, i.e., 100% of participants from each age group were used in the training datasets. We used only half of the participants from each age group in the training datasets for user-independent with 50% training data. Likewise, we used only one participant from each age group in the training datasets for user-independent with data from one participant as training data. We evaluated the classification accuracy results of individual metrics as well as their combinations to measure the influence of gesture features on the age-group classification accuracy on different screen sizes under difference scenarios.

7.5.1 User-Dependent Age-group Classification (training with all participants)

Effect of Age: Table 24 below shows the classification results for users of the two age groups. In analysing single features, gesture speed achieved the highest classification accuracy of 63% (see arrow-up) for elderly users, and gesture accuracy resulted in the lowest classification accuracy of 39% (see arrow-down). For younger users, the highest classification accuracy (94%, see arrow-up) was achieved with MT whilst the FP resulted in the lowest classification accuracy (74%, see arrow-down).

With combined features, the highest classification accuracy (59%), for elderly users was achieved with gesture accuracy, FP, and speed. The lowest classification accuracy (52%) was achieved with gesture accuracy, FP, and MT. For younger users, the highest classification accuracy of 94% was achieved with gesture accuracy, FP, and MT. The lowest classification accuracy (86%) was based on gesture accuracy, FP, and speed. In general, combinations gesture-based features have had a positive effect on the classifications accuracy for younger users – the classification accuracy improved from 74% to 86%. Also, the lowest classification accuracy for elderly users improved from 39% to 52% using a combination of features.

Table 24. User's age-group classifications research results for user-dependent (100%) of ageing influence. Arrow up shows larger value, and arrow down shows lower values.

Analysis	Feature	Age Groups	
		EG	YG
Individually	Speed	63.20% ↑	82.40%
	Gesture accuracy	39.20% ↓	92.80%
	FP	58.40%	73.60% ↓
	MT	50.40%	94.40% ↑
Combinations	Gesture accuracy, FP	52.00%	92.80%
	Gesture accuracy, FP, Speed	59.20% ↑	85.60% ↓
	Gesture accuracy, FP, MT	52.00% ↓	94.40% ↑
	Gesture accuracy, FP, MT, Speed	55.20%	92.00%
	Gesture accuracy, Speed	56.80%	86.40%
	FP, MT, Speed	56.00%	88.00%
	MT, Speed	56.00%	89.60%

The above results reveal that the classification accuracy is higher for younger users than it is for elderly users. This indicates that the performance of some elderly users was similar to the younger users' performance. Note that Minocha et al. (Minocha, et al., 2013) concluded that not all elderly people are vulnerable in performing technology tasks. Our research provides evidence for the possibility of classifying user's age-group based on touch-gestures. Also, the combinations of features have improved the classification accuracy.

Screen Size Influence: Table 25 shows the classification results for the two screen sizes across two age groups. In analysing single features, the gesture speed achieved the highest classification accuracy of 85% (see arrow-up) and FP resulted in the lowest classification accuracy of 62% (see arrow-down) for the users of two age groups on small smartphone. On the mini-tablet, the highest classification accuracy (70%, see arrow-up) was achieved with FP whilst the gesture accuracy resulted in the lowest classification accuracy (53%, see arrow-down).

With combined features, the highest classification accuracy of 86% was achieved on small smartphone with gesture accuracy, FP, and speed. The lowest classification accuracy (77%) was achieved with gesture accuracy, FP, and MT. On the mini-tablet, the highest classification accuracy (69%) was achieved with gesture accuracy, FP, and MT. The lowest classification accuracy (58%) was based on gesture accuracy, FP, and speed.

Table 25. User's age-group classifications research results for user-dependant (100%) of screen sizes influence. Arrow up shows larger value, and arrow down shows lower values.

Analysis	**Feature**	**Screen Sizes**	
		Small Smartphone	**Mini-tablet**
Individually	Speed	85.38% ↑	59.17%
	Gesture accuracy	78.46%	52.50% ↓
	FP	62.31% ↓	70.00% ↑
	MT	75.38%	69.17%
Combinations	Gesture accuracy, FP	80.77%	63.33%
	Gesture accuracy, FP, Speed	86.15% ↑	57.50% ↓
	Gesture accuracy, FP, MT	76.92% ↓	69.17% ↑
	Gesture accuracy, FP, MT, Speed	80.00%	66.67%
	Gesture accuracy, Speed	83.85%	58.33%
	FP, MT, Speed	80.00%	63.33%
	MT, Speed	80.00%	65.00%

The results reveal that the classification accuracy is higher on small smartphone than on the mini-tablet. This is could be very much linked to the difficulties face by elderly users in using small smartphones compared to large sizes. In general, combining gesture-based features had a positive effect on the classification accuracy – the lowest classification accuracy on the mini-tablet improved from 53% to 58%. Also, the lowest classification accuracy on the small smartphone improved from 62% to 77%. Our research provides clear evidence for the possibility of classifying user's age-group based on touch-gestures, especially on small smartphones – further investigation is necessary to identify suitable discriminant features/metrics for large screen sizes.

7.5.2 User-Independent Age-group Classification (training with 50% of participants)

In this experiment, we wanted to evaluate the age-group classification accuracy based on participants that were not in the training set to simulate real-life application scenarios. For example, a user interacting with a smartphone/tablet device at a shopping centres to find product information. In this experiment scenario, training data consist of only 50% of the participants from each age group. The results presented in Table 26 and Table 27 show that the system can classify the user's age-group with no significant difference accuracy classification between user-independent and user-dependent scenarios.

Effect of Age:

Table 26 below shows the classification results for users of the two age groups. In analysing single features, *gesture speed* achieved the highest classification accuracy of 61% (see arrow-up) for elderly users, while the *gesture accuracy* resulted in the lowest classification accuracy of 46% (see arrow-down). For younger users, the highest classification accuracy (90%, see arrow-up) was achieved with *gesture accuracy* whilst FP resulted in the lowest classification accuracy (75%, see arrow-down).

With combined features, the highest classification accuracy (57%) for elderly users was achieved with FP, MT, and *gesture speed*. The lowest classification accuracy (46%) was achieved with *gesture accuracy*, and *speed*. For younger users, the highest classification accuracy of 91% was achieved with two different of combinations: 1) *gesture accuracy*, and FP, 2) *gesture accuracy*, FP, and *gesture speed*. The lowest classification accuracy (88%) was based on FP, MT, and *gesture speed*.

As in the user-dependent scenario, the results revealed that the classification accuracy is higher for younger users than it is for elderly users. This indicates that the performance for some elderly is similar to the younger users' performance. In general, combining gesture-based features had a positive effect on the classification accuracy for younger users - the lowest classification accuracy with a single feature increased from 75% to 88%. The research provides evidence for the possibility of classifying user's age-group based on touch-gesture, even with a small number of participants in the training datasets and they did not include the user in question.

Table 26. Age-group classifications research results for User-Independent metrics (50%) of ageing influence. Arrow up shows larger value, and arrow down shows lower values.

Analysis	Feature	Age Groups	
		EG	YG
Individually	Speed	60.80% ↑	82.40%
	Gesture accuracy	45.60% ↓	90.40% ↑
	FP	56.80%	75.20% ↓
	MT	55.20%	89.60%
Combinations	Gesture accuracy, and FP	52.80%	91.20% ↑
	Gesture accuracy, FP, Speed	53.60%	91.20% ↑
	Gesture accuracy, FP, MT	56.00%	88.80%
	Gesture accuracy, FP, MT, Speed	56.00%	89.60%
	Gesture accuracy, Speed	46.40% ↓	90.40%
	FP, MT, and Speed	56.80% ↑	88.00% ↓
	MT, and Speed	56.00%	89.60%

Screen Size Influence:

Table 27 shows the classification results for the two screen sizes across the two age groups. In analysing single features, *gesture speed* achieved highest classification accuracy of 85% (see arrow-up) on small smartphones, and the FP resulted in the lowest classification accuracy of 62% (see arrow-down). On the mini-tablet for the users of the two age groups, the highest classification accuracy (71%, see arrow-up) was achieved with FP whilst the gesture accuracy resulted in the lowest classification accuracy (53%, see arrow-down).

With combined features, the highest classification accuracy (82%), on small smartphone was achieved with *gesture accuracy* and *gesture speed*. The lowest classification accuracy (81%) was achieved with FP, MT, and *gesture speed*. On mini-tablet, the highest classification accuracy (63%) was achieved with three different combinations: 1) *gesture accuracy*, FP, MT, and *gesture speed*; 2) FP, MT, and *gesture speed;* and 3) MT, and *gesture speed*. The lowest classification accuracy (53%) was based on *gesture accuracy*, and *gesture speed*.

The results reveal that the classification accuracy is higher on the small smartphone than it is on the mini-tablet reflecting the difficulties in using small smartphones compared to mini-tablet. In general, combining gesture-based features had a positive effect on the classification accuracy – the lowest classification accuracy with a single feature increased from 62% to 81%. The results of users-independent (50%) age-group classification accuracy are slightly similar to the results in user-dependent (100%) scenario. This provides further evidence to the possibility of classifying user age-group on different smartphones screen sizes, even if the number of participants in the training datasets was fewer and did not include users' training.

Table 27. Age-group classifications research results for User-Independent metrics (50%) of screen size influence. Arrow up shows larger value, and arrow down shows lower values.

Analysis	Feature	Screen Sizes	
		Small smartphone	Mini-tablet
Individually	Speed	84.62% ↑	57.50%
	Gesture accuracy	81.54%	53.33% ↓
	FP	61.54% ↓	70.83% ↑
	MT	79.23%	65.00%
Combinations	Gesture accuracy, and FP	81.54%	61.67%
	Gesture accuracy, FP, Speed	81.54%	62.50%
	Gesture accuracy, FP, MT	81.54%	62.50%
	Gesture accuracy, FP, MT, Speed	81.54%	63.33% ↑
	Gesture accuracy, Speed	82.31% ↑	53.33% ↓
	FP, MT, and Speed	80.77% ↓	63.33% ↑
	MT, and Speed	81.54%	63.33% ↑

7.5.3 User Independent (training with participant)

In this experiment, we want to evaluate the scenario where only limited number of participants are available to collect training. Therefore, we used the gesture data of one participant from each age group to create the training datasets. The results presented in Table 28 and Table 29 show that the system can classify users' age-group using a small number of training data and still achieve a reasonable classification accuracy compared to user-dependent (100%) or user-independent (50%) scenarios we presented earlier.

Effect of Age: Table 28 below shows the age-group classification results for users of the two age groups. In analysing single features, *gesture speed* achieved the highest classification accuracy of 74% (see arrow-up) for elderly users, and the MT resulted in the lowest classification accuracy of 42% (see arrow-down). For younger users, the highest classification accuracy (96%, see arrow-up) was achieved with MT whilst and *gesture speed* resulted in the lowest classification accuracy (72%, see arrow-down).

With combined features, the highest classification accuracy (70%), for elderly users was achieved with two different feature combinations: 1) *gesture accuracy*, FP, and *gesture speed*, 2) *gesture accuracy*, and *gesture speed*. The lowest classification accuracy (42%) was achieved with *gesture accuracy*, FP and MT. For younger users, the highest classification accuracy of 97% was achieved with *gesture accuracy*, FP, and MT. The lowest classification accuracy (75%) was based on *gesture accuracy*, and *gesture speed*.

Table 28. User's age-group classifications research results for User-Independent metrics (1 participant) of ageing influence.

Analysis	Features (metrics)	Age Groups	
		EG	YG
Individually	Speed	74.40% ↑	72.00% ↓
	Gesture accuracy	45.60%	76.80%
	FP	52.00%	83.20%
	MT	42.40% ↓	96.00% ↑
Combinations	Gesture accuracy, and FP	43.20%	92.00%
	Gesture accuracy, FP, Speed	69.60% ↑	80.80%
	Gesture accuracy, FP, MT	42.40% ↓	96.80% ↑
	Gesture accuracy, FP, MT, Speed	56.80%	93.60%
	Gesture accuracy, Speed	69.60% ↑	75.20% ↓
	FP, MT, Speed	56.00%	93.60%
	MT, Speed	53.60%	93.60%

As in the previous scenarios, the results of this experiment show that the classification accuracy is higher for younger users than it is for elderly users. In general, combining gesture-based features had a positive effect on the classification accuracy for younger users - the highest classification accuracy with a single feature increased from 96% to 97%. Also, the lowest classification for younger users the accuracy improved from 72% to 75%. The research provides further evidence for the possibility of classifying users' age-group based on touch-gestures, even if the numbers of participants in training datasets were very small.

Screen Size Influence. Table 29 shows the classification results for the two screen sizes across the two age groups. In analysing single features, *gesture speed* achieved the highest classification accuracy of 86% (see arrow-up) on the small smartphone, whilst FP resulted in the lowest classification accuracy of 65% (see arrow-down). On the mini-tablet, the highest classification accuracy (70%, see arrow-up) was achieved with FP whilst the *gesture accuracy* resulted in the lowest classification accuracy (56%, see arrow-down).

Table 29. User's age-group classifications research results for User-Independent metrics (1 participant) of screen sizes influence.

Analysis	Features (metrics)	Screen Sizes	
		Small smartphone	mini-tablet
Individually	Speed	86.15% ↑	59.17%
	Gesture accuracy	66.15%	55.83% ↓
	FP	65.38% ↓	70.00% ↑
	MT	77.69%	60.00%
Combinations	Gesture accuracy, and FP	76.92% ↓	57.50% ↓
	Gesture accuracy, FP, Speed	90.00% ↑	59.17%
	Gesture accuracy, FP, MT	77.69%	60.83% ↑
	Gesture accuracy, FP, MT, Speed	88.46%	60.83% ↑
	Gesture accuracy, Speed	85.38%	58.33%
	FP, MT, Speed	87.69%	60.83% ↑
	MT, Speed	85.38%	60.83% ↑

With combined features, the highest classification accuracy (90%), on the small smartphone was achieved with *gesture accuracy*, FP, and *gesture speed*. The lowest classification accuracy (77%) was achieved with *gesture accuracy*, and FP. On the mini-tablet, the highest classification accuracy of 61% was achieved with four different feature combinations: 1) all four features together; 2) *gesture accuracy*, FP, and MT; 3) FP, MT, and *gesture speed*; and 4) MT, and *gesture speed*. The lowest classification accuracy (58%) was based on *gesture accuracy* and FP.

The results demonstrate that the classification accuracy is higher on the small smartphone than it is on the mini-tablet – gesture performance on large screen sizes is relatively similar for the different age groups. In general, taking a combination of gesture-based features has had a positive effect on the classification accuracy – on the small smartphone, the highest classification accuracy with a single feature increased from 86% to 90% and the lowest classification accuracy with a single feature improved from 65% to 77%. In addition, the lowest classification accuracy on mini-tablets improved from 56% to 58 %.

The results of users-independent experiment are similar to the results achieved in user-dependent scenario. These results provide further evidence for the possibility of classifying users' age-group on smartphones, even if the number of participants in the training datasets is very minimal.

7.6. Chapter Conclusion and Summary

This chapter conducted experiments to provide evidence for the possibility of classifying users' age-group based on gesture-based features on smartphones and tablets. Based on the research discussed in Chapter 6, four gesture-based metrics (i.e., gesture accuracy, gesture speed, movement time, and finger pressure) from (the research in Section 6.2) were identified as features to use in age-group classification. NN classification was used to classify a given user's age-group. The research included 25 elderly, and 25 younger participants and eight gestures. Classification accuracy for user-dependent and user-independent training scenarios were considered. In each scenario, we analysed the four metrics individually as well as in combination to evaluate their ability to distinguish users as belonging to one of two age-groups.

The results of the highest and lowest classification accuracies for elderly and younger users based on the three scenarios presented in Table 24 - Table 29 are summarised in Table 30. Also, the results of the small smartphone and the mini-tablets based on the three scenarios presented in Table 24 - Table 29 are summarised in Table 31. These summarised results provide evidence for the possibility of classifying users' age based on touch-gestures – this is as was expected in hypotheses H15 and H16. In addition, combinations gesture-based features have improved classifications accuracy.

Our analysis showed that age-group classification based on the four features is higher on the small smartphone compared the mini-tablet size. This is because, as we found in the previous chapter, the gesture performance on the small smartphone was different for the two age-groups – elderly were particularly slow, less accurate and exerted more pressure on the screen than the younger users. On the other hand, less significant differences in gesture performance were found for the two age groups on the mini-tablet.

Table 30. Summary results for age influence on user's age-group classifications.

Analysis			EG			YG		
			1	50%	100%	1	50%	100%
Individually	Highest	Metrics	Speed	Speed	Speed	MT	Acc	MT
		Results	**74%**	**61%**	**63%**	96%	90%	94%
	Lowest	Metrics	MT	Acc	MT	Speed	FP	FP
		Results	42%	46%	50%	74%	75%	74%
Combinations	Highest	Metrics	(Acc, FP, speed) (Acc, speed)	(MT, FP, speed)	(Acc, FP, speed)	(Acc, FP, MT)	(Acc, FP) (Acc, FP, speed)	(Acc, FP, MT)
		Results	70%	57%	59%	97%	91%	94%
	Lowest	Metrics	(Acc, FP, MT)	(Acc, speed)	(Acc, FP, MT)	(Acc, speed)	(MT, FP, speed)	(Acc, FP, speed)
		Results	42%	46%	52%	75%	88%	85%

Table 31. Summary results for screen size influence on user's age-group classifications.

Analysis			Small smartphone			mini-tablet		
			1	50%	100%	1	50%	100%
Individually	Highest	Metrics	Speed	Speed	Speed	FP	FP	FP
		Results	86%	**85%**	85%	**70%**	**70%**	**71%**
	Lowest	Metrics	FP	FP	FP	Acc	Acc	Acc
		Results	65%	62%	62%	56%	53%	52%
Combinations	Highest	Metrics	(Acc, FP, Speed)	(Acc, speed)	(Acc, FP, speed)	(All) (Acc, FP, MT) (FP, MT, speed)	(All)	(Acc, FP, MT)
		Results	90%	82%	86%	61%	63%	69%
	Lowest	Metrics	(Acc, FP)	(FP, MT, speed)	(Acc, FP, MT)	(Acc, FP)	(Acc, speed)	(Acc, FP, speed)
		Results	77%	81%	76%	58%	53%	58%

The age-classification results show that it was relatively easier to classify younger users than the older ones. This because the gesture performance of most younger users were similar to each other, where as some elderly users, probably due to their experience, were able to perform gestures with similar characteristics to younger users – a significant number of elderly users were misclassified as belonging to the younger age-group.

Using a combination of gesture features in the classification process improved the classification accuracy when compared to using a single feature. The results for all three scenarios remained close to each other indicating that the age-group classification can be performed with reasonable accuracy by using only a small number of training samples and these does not have to belong to the user.

We have proposed the use of touch-gesture based features on smartphones to classify users' age-group and have demonstrated the viability of such a scheme through a number of experiments. A comprehensive set of experiments with detailed analysis is required to identify other useful gesture based features for age-group classification. To the best of our knowledge we have not come across any study conducted on smartphones to classify age-group using gesture-based features.

The next chapter – the concluding chapter of the thesis – presents a general overview of the thesis and a summary discussing results of the five studies. The chapter will discuss the limitations and challenges of the study and will conclude with a list of contributions and the implications of the study, followed by directions of future work.

CHAPTER 8

GENERAL DISCUSSIONS AND FUTURE WORK

User Interfaces (UI) play an important role in HCI especially in smartphones and tablets. Due to the increased population of elderly people (60+) in the world, and the widespread use of smartphone technologies, it is extremely important to understand the effects of age on the usability of rapidly evolving smartphone technology. Studies in HCI are required to minimise the "digital divide" between elderly users who are known to suffer from physiological and psychological impairments, and younger users who adopt technology faster. Eye movement is being increasingly used in HCI research to provide empirical evidence on evaluation the usability of technology because of its high gaze accuracy. Touch-gestures has become the most common method of interaction with applications on modern smartphones and tablets.

The aim of this thesis was to provide an insight into the effects of age on interactions with smartphone and tablet applications. Five studies were conducted to understand the difficulties that elderly users encounter when they interact with smartphones and their applications. Studies were conducted on two interactions methods; eye-movement tracking, and touch-gestures using smartphones/tablets of three screen sizes.

This chapter presents a general overview of our work and a discussion of results from the five studies that make up this thesis. We will discuss challenges and the general limitations of the study. The chapter, and in turn the thesis will conclude by listing the contributions and the implications of the study, followed by our future direction of work. Our findings aims provide the literature with a theoretical and an empirical account of visual search behavior and touch-gestures for elderly users on smartphones.

8.1. Motivation

The motivations for conducting the research studies in this thesis can be summarized as follows:

- Elderly population in our society is increasing; there are more people in the UK who are 60+ than people who are aged below 18 years old. According to a recent UN report (UN, 2013), the total number of persons aged over 60 years old increased from 9.2 % in 1990 to 11.7 % in 2013 and this is projected to double by 2050.
- The technology use is widespread across the world and a significant percentage of elderly people now use a smartphone/tablet device for a variety of application. For example, 39% of 60+ years old now own a smartphone and 21 percent of 70-79 years old own a tablet device (Consulting, 2013). Such technology can assist elderly users in their activities of daily lives and increase their quality of life (e.g. healthcare monitoring, social isolation) (Minocha, 2013), (Minocha, et al., 2013).
- Understanding the usability issues faced by the elderly people using smartphone applications is important in order to make it easier for them use smartphone applications (Balakrishnan, et al., 2012), (Caprani, et al., 2012), (Reddy & Chattopadhyay, 2014).
- Provide the existing body of literature with new understanding on the effects of ageing on smartphone usability.

8.2. Study Stages

The thesis includes five studies that were conducted in two stages. This section provides a brief overview of the stages and the respective studies.

8.2.1 Stage One

This stage investigated the effects of ageing and the influence of screen size on users based on smartphone interface browsing using eye movement tracking. This stage included researches to address the following question:

What is the effect of age in browsing smartphone applications using eye movements? (H1 – H4).

The **First Research** investigated the scan-path dissimilarities when browsing smartphone applications by participants from elderly (EG), and younger (YG) age groups. The results revealed that there is an ageing effect on scan-path dissimilarities when browsing smartphones applications – higher scan-path dissimilarities were found for elderly users.

The results also revealed that browsing applications was stimulus-driven rather than screen sizes-driven.

The **Second Research** investigated the local and global information processing difficulties when browsing smartphone applications by elderly, middle-age and younger users. The results revealed that elderly users faced difficulties in local and global information processing because of the design of smartphone applications compared to users of other ages. Furthermore, the users' performance efficiency was higher on large screen sizes (e.g. tablet size) compared to small screen sizes.

In general the results of both researches revealed a possible relationship between getting older with less experience in using smartphones, smaller screen sizes, and the complexity of interface design with smaller screen sizes of smartphones. This leads the users having high dissimilarity in browsing and had difficulties in information processing. The difficulties were in local information processing measured by fixation duration for spending long time in recognising interface contents, and also in global information processing measured by scan-path duration for difficult interface structure.

8.2.2 **Stage Two**

This stage investigated the effects of ageing and the influence of screen size on users based on gesture-based applications on smartphones/tablets. Stage two included three researches:

The **First Research** investigated the effects of ageing on gesture swiping performance. This section addressed the following question:

> *To what extent could elderly perform gesture swiping on smartphone interfaces without needing to training? (H5 & H6)*

In this research we found a relationship between the increasing of user age, with lack of experience, and smaller screen sizes. The results showed that elderly users were less efficient in performing gesture swiping tasks, their gesture swipes were less smooth, and they exerted more force pressure than younger users. In addition, the elderly were significantly less efficient in performing vertical gesture swiping, but not so when performing horizontal gesture swiping. Moreover, the small smartphone was less usable in terms of gesture swiping for users of both age groups, more so for elderly.

The **Second Research** used gesture-based features to investigate the effects of user age, smartphone screen-size and gesture complexity on performing accurate gestures. This section addressed the following question:

> *What is the effect of age on executing accurate gestures on smartphones using gesture based applications? (H7 – H14)*

In this research, we found a relationship between the increasing of user age, lack of experience, smaller screen sizes, and complex gestures. The results showed that elderly users were significantly less accurate in performing touch gestures – worse on the small smartphone. Also, elderly users were less efficient, and they exerted significantly more force pressure compared to the younger users. The users of two age groups were significantly less efficient and less accurate when performing complex gestures on small smartphone compared to the mini-tablet.

The **Third Research** investigated the possibility of classifying user's age-group using gesture-based applications on smartphones/tablets. This section addressed the following question:

> *Could we use gestures performed on smartphone applications to classify user age? (H15 & H16)*

Four gesture-related features (i.e., gesture accuracy, movement time, speed, and finger pressure) were extracted from the second research of this stage to use in the age-group classification research. Three different scenarios were evaluated to test the effectiveness of the four features for age-group classification. These were: classification with prior knowledge of the individual user's behaviour (i.e., user-dependent age-group classification -100% of participants) and classification with no prior knowledge of the individual user's behaviour (i.e., user-independent age-group classification - 50% and 1% of participants). On each of three scenarios, we considered the classification performance of individual features separately as well as their combinations.

Experimental results revealed that it is possible to classify a user's age-group based on user's touch-gesture features. The classification accuracy was higher for younger users than it was for elderly users. This is because most of younger users performed gestures similar to each other, where as some elderly users' gestures performance were similar to younger users, thereby getting misclassified as belonging to the younger age group. Also, the classification accuracy was higher on a small smartphone than on a mini-tablet. This is because small smartphones was difficult for all users in general compared to mini-tablets.

Results provided evidence for the possibility of classifying user age-group on different screen sizes of smartphones. It was possible to classify user age-group without prior knowledge of the individual user. Also, the combinations of metrics (or feature-fusion) enhanced the classification accuracy compared to individually metrics. The best features for combination are gesture accuracy, finger pressure, movement time, that were on user-independent scenario (1%) for younger users at (i.e., 97%), and the least classification accuracy was on the same scenario and features for elderly users at (42%).

The outcomes of this particular research could be used to develop a system that can adapt itself to the particular user's needs based on his/her ability.(i.e., the system will turn into a particular setting based on its current user's age-group). This could be helpful in particular to users who are unable to setup their own smartphone, tablet or a similar device to their own preferences, or for a public system that could be used by different users at different times (e.g. touchscreen devices in the shopping centre used to find a particular shop, or those that are used in the hospital or GP that used for self check-in system).

8.3. Contributions

Our contributions in the thesis can be highlighted as key contributions, and secondary contributions.

8.3.1 Key Contributions

In terms of eye movement tracking and touch-gestures on smartphones and tablets for elderly users, our studies provides a theoretical and an empirical account of visual search behaviour and touch-gesture interactions to the existing body of literature.

The four major contributions of this thesis are:

1. *An in-depth understanding of difficulties that elderly users experience when browsing smartphones applications.* Experimental findings provided empirical evidence of interaction difficulties that elderly users experience on smartphones applications;

elderly users were slower and have difficulties in information processing, exerted more force pressure, and exhibited less efficient search compared to other age groups. This thesis provides evidence linked to the elderly deficits and limitations.

2. *Provided evidence of how elderly use finger gestures on touchscreens when interacting with applications on small smartphones and tablet.* In this thesis, more details are provided about elderly difficulties when performing gesture swiping on smartphones and mini-tablets devices. These researches are considered as the first work conducted on gesture-based applications using small smartphones and mini-sized tablets for elderly users, which will add to the existing body of literature with both theoretical and empirical researches in the field of HCI and usability of smartphone for elderly users using gesture-based applications.
3. *Provided evidence of how elderly use eye-movement when interacting with smartphone applications.* In this thesis, eye-movement tracking was used to provide more details about elderly difficulties when browsing smartphones. This included scan-path string dissimilarity and difficulties at both local and global information processing on smartphones interfaces browsing for elderly users. Our work is considered as the first work conducted on eye-movement using small smartphones and mini-sized tablets for elderly users, which will add to the existing body of literature with both theoretical and empirical researches in HCI and usability of smartphone for elderly using eye movement.
4. *Evidence of the possibility of classifying users' age-group using features extracted from user's touch gestures on smartphones.* In this thesis, evidence for the possibility of classifying users' age-groups based on a user's ability using gesture-based features on smartphones and tablets devices is provided.

8.3.2 Secondary Contributions

Beyond the experimental results, the contributions of this thesis within the scope of HCI and smartphone usability contexts are:

1. *Providing a study that could work as a system for user's age-group classification using gesture-based feature on smartphones.*
2. *Providing new experimental procedures and analysis methods in gesture accuracy research.* In our research, the users were asked to execute the gestures on a displayed

path on the smartphones. In addition, DTW algorithm was used to calculate the distance between the reference data and data obtained from the participants. The experiment procedure and algorithm used in the analysis are new in this field of research.

8.4. Implications and Recommendations of the Study

The implications and recommendations of our study can be listed as follows:

- Consider the force pressure applied on smartphone touch screens by elderly users to improve the touchscreen's response to touch gestures taking in to account elderly users' reduced movement ability, and sensory perception of touch. It was shown from the researches in Chapter 6 that elderly exerted more force pressure on smartphones than younger users. We suggest to consider user age-group classification work to solve force pressure problem when designing touchscreen for the elderly. This is to enhance the usability of smartphones for elderly users because the response of technology does not meet elderly ability when executing gestures. This is to be equally efficient for elderly as it is for younger users.
- Eliminate unnecessary complex gestures and use simple gestures (i.e., employ single-line gestures without a lot of corners and curves) to interact with smartphone applications, especially the ones designed for elderly users to assist in the activities of their daily lives.
- Make elderly users familiar with smartphone applications by providing them training on new designs of interface contents. This could be done by the carers of elderly people.
- Training of elderly on touch-gesture patterns is required. This could be done by the carers of elderly people. Also, training them on not to press hard on the touchscreen will reduce errors when performing tasks.
- Consider devices with large screen sizes for applications designed specifically for elderly users.
- Mobile apps developers should consider designing applications in landscape orientation.
- Consider adapting the device/application by its self to accommodate user's ability when executing gestures based features in the public system. This will make the

device/application customise its self to the particular setting to enhance the usability of the devices/application for elderly, particularly when such devices are used in public places.

8.5. Limitations of the Study

We acknowledge that there are a number of limitations in our study. Some are due to time and resources limitations while others relate to methodology. The main limitations are:

1. Smartphone applications used in the eye-movement analysis study had to be displayed as screenshots on a PC screen. Ideally, we would have liked to use an eye-tracker device that can analyse participants' eye-movements as they browsed applications on the smartphone itself (e.g. a head-mounted eye-tracker). Nevertheless, ours is one of the few studies that used an eye-tracker device to analysis application browsing behaviours of elderly. (eye-movement tracking researches)

2. The representation of users' experience when using smartphones and tablets could be refined. For example, one user might have used/owned a smartphone for a longer period, but used only occasionally and for few basic applications (e.g. call, text, camera), whereas another user may have used/owned smartphone for a shorter period than the first user, but much more frequently and for a many applications (e.g. call, text, email camera, social networking, social media, internet browsing). (eye-movement tracking and touch-gestures researches)
3. Limited numbers of gestures were used to collect data. In particular, the circle and the triangle gestures could have been performed clock-wise and anti-clock-wise. Furthermore, we have not considered pinch and zoom gestures that are commonly used to interact with smartphone applications. (gesture accuracy research)
4. Consideration of the influence of finger size was limited. Also, we have not considered the influence of finger length on gesture performance – it could be argued that finger length could affect gesture length, movement time and speed. (touch-gestures researches)
5. Small number of participants, in particular participants in the elderly age group. Since we did not want to use the same participant to collect data on different screen

sizes, we had to find many participants from each age group, which was a difficult task. Although the numbers were relatively small, our study is based on data acquired from far more participants than those used in other studies. (eye-movement tracking and touch-gestures researches)

6. Consideration of left handed and right handed for the users were limited. Also, we have not considered the influence of hand-held use in performing gestures on smartphones – it would be useful to investigate the influence of hand-held use on user's performance. (touch-gestures researches)
7. Consideration of education level of participants was limited. This required large number of participants to cover a range of education levels for the participants in order to investigate the influence of participants' education on their performance. (eye-movement tracking and touch-gestures researches)
8. Consideration of participants' vision sensitivity and physical-ability were limited. Relevant information can be collected based on reports provided by participants. (eye-movement tracking and touch-gestures researches)
9. We have some limitations in our analysis, as we did not look at performances at individual participant level. We conducted the work only on average results for each age group. (eye-movement tracking and touch-gestures researches)

8.6. Future Work

In future, we intend to conduct further studies on touch-gestures and eye movement tracking for users of different age groups. The following are some of the work we intend carry out starting with addressing a limitation of the current study.

- Analyse the effects of finger-size on user efficiency and accuracy when performing touch gestures on smartphones of different sizes. Metrics to consider are finger base circumference, fingertip circumference, finger length, and hand span. A number of complex and non-complex gestures should be considered as part of this future study.
- Investigate the influence of user experience on performance using large sample size of participants. This is to involve users of different ages and group them based on specific experience e.g. experience in using smartphones, frequency of smartphone use, experience on specific applications. In addition, investigate the influence of user

training on touchscreens and measure accuracy and force pressure when executing gestures on touchscreen.

- Conduct further investigation on elderly users who have high efficiency and high performance accuracy. This is to analysis the individual level results for users. Also, the same investigation on younger users to analysis the individual level results for users who have less efficiency and less performance accuracy.
- Investigate the possibility of employing the 8 gestures we used in the research in Section 6.2 as commands to control smartphone applications. For example, using the circle gesture to save a file, the triangle gesture to open a file, and so on.
- Extend the work of touch-gesture based age-group classification to smartphone user identification (i.e., user touch-gesture as a biometric). This could be used to enhance the security of screen pattern based unlock system used in most smartphones.
- Investigate smartphones and tablets usability based on multi-touch gestures (e.g. pinching, dragging, zooming-in and zooming-out on online maps). Such a study is required to understand the nature of the challenge faced by elderly users when executing gestures using multiple fingers.
- Investigate the influence of each of the following cases: user education, and hand-handled that used to perform tasks on users performance.

References

AgeUK, 2015. *Later Life in the United Kingdom*, UK. [Online] Available at: http://www.ageuk.org.uk/Documents/ENGB/Factsheets/Later_Life_UK_factsheet.pdf?dtrk =true *(accessed 27 January 2015)*.

Akl, A. & Valaee, S., 2010. *Accelerometer-based gesture recognition via dynamic-time warping, affinity propagation, & compressive sensing.* IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), 2010, pp. 2270-2273.

Alleyne, R., 2010. *Middle age begins at 35 and ends at 58.* [Online] Available at: http://www.telegraph.co.uk/health/healthnews/7458147/Middle-age-begins-at-35-and-ends-at-58.html *(accessed 27 January 2015)*.

Al-Wabil, A., 2009. *The Effect of Dyslexia on Web Navigation*, Centre for Human-Computer Interaction Design, City University London, United Kingdom, PhD Thesis 2009.

Al-Wabil, A., Zaphiris, P. & Wilson, S., 2008. *Examining visual attention of dyslexics on web navigation structures with eye tracking.* International Conference on Innovations in Information Technology, 2008. IIT 2008, pp. 717-721.

Andrienko, G., Andrienko, N., Burch, M. & Weiskopf, D., 2012. Visual Analytics Methodology for Eye Movement Studies. *IEEE Transactions on Visualization and Computer Graphics,* 18(12), pp. 2889-2898.

Arning, K., Gaul, S. & Ziefle, M., 2010. *Same Same but Different How Service Contexts of Mobile Technologies Shape Usage Motives and Barriers.* HCI in Work and Learning, Life and Leisure. Springer Berlin Heidelberg, pp. 34-54.

Arnott, J., Khairulla, Z., Dickinson, A., Syme, A., Alm, N., Eisma, R. & Gregor, P., 2004. E-mail interfaces for older people. Dundee, Scotland, U.K, IEEE International Conference on Systems, Man and Cybernetics, 2004. University of Dundee, pp. 111 -117 vol.1.

Artis, S., 2004. *Effects of Age and Working Memory on Web-Based Computer Training.* IEEE Symposium on Visual Languages and Human Centric Computing, 2004, pp. 269-270.

Balakrishnan, S., Salim, S. & Hong, J. L., 2012. *User Centered Design Approach for Elderly People in Using Website.* International Conference on Advanced Computer Science Applications and Technologies (ACSAT), 2012, pp. 382-387.

Benoit, O., Marc, K., Fernand, F., Dieter, F., & Martine, H., 2009. *User-centered activity management system for elderly people Empowering older people with interactive technologies to manage their activities at the retirement home.* 3rd International Conference on Pervasive Computing Technologies for Healthcare, 2009. PervasiveHealth 2009, pp. 1-4.

Bhuiyan, M. & Picking, R., 2009. *Gesture-controlled user interfaces, what have we done and what's next?.* Proceedings of the Fifth Collaborative Research Symposium on Security, E-Learning, Internet and Networking (SEIN 2009), Darmstadt, Germany, pp. 26-27.

Bikson, K. L. & Bikson, T. K., 2001. The impact of Internet use over time on older adults: A field experiment. *Communication, technology and aging: Opportunities and challenges for the future,* pp. 127-149.

Broder, A., 2002. *A taxonomy of web search.* ACM Sigir forum, pp. 3-10.

Caprani, N., O'Connor, N. E. & Gurrin, C., 2012. Touch screens for the older user. *Assistive Technologies, Dr. Fernando Auat Cheein (Ed.).*

Card, S. K., Newell, A. & Moran, T. P., 1983. *The Psychology of Human-Computer Interaction.* Hillsdale, NJ, USA: L. Erlbaum Associates Inc.

Cavanaugh, J. & Blanchard-Fields, F., 2005. *Adult development and aging.* Five Edition. Cengage Learning.

Chen, W., 2013. *Gesture-Based Applications for Elderly People.* Human-Computer Interaction. Interaction Modalities and Techniques. Springer Berlin Heidelberg, pp. 186-195.

Consulting, D. S., 2013. New generation of older shoppers 'defy stereotypes'. Digital Strategy Consulting Limited. [Online] Available at: http://www.digitalstrategyconsulting.com/intelligence/2013/12/new_generation_of_older_shoppers_defy_stereotypes.php *(accessed 26 Feberuary 2015).*

Cooke, L., 2006. Is Eye Tracking the Next Step in Usability Testing?. *0-7803-9778-9/06/$20.00 ©2006 IEEE,* p. 7.

Deardorff, C. J. & Birdsong, C., 2003. Universal design: clarifying a common vocabulary. *Housing and Society*, 30(2), pp. 119-138.

Deloitte, 2014. The smartphone generation gap: over-55? there's no app for that. Deloitte Touche Tohmatsu Limited-London.

Dhillon, J., Ramos, C., Wunsche, B. & Lutteroth, C., 2011. *Designing a web-based telehealth system for elderly people: An interview study in New Zealand.* 24th International Symposium on Computer-Based Medical Systems (CBMS), 2011, pp. 1-6.

DIX, A., FINLAY, J., ABOWD, G. D. & BEALE, R., 2004. *HUMAN COMPUTER INTERACTION.* Third Edition: British Library Catalouing in Publicating Data.

Downton, A., 1991. *Engineering The Human-Computer Interface.* McGRAW-HILL BOOK COMPANY.

Duchowski, A. T. et al., 2010. *Scanpath comparison revisited.* Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications. ACM, pp. 219-226.

Duval, S., Hoareau, C. & Hashizume, H., 2008. *Age in Ubiquitous Computing: A Thin Thread.* Third International Conference on Convergence and Hybrid Information Technology, 2008. ICCIT '08, pp. 423-429.

Dyk, T. V., Gelderblom, H., Renaud, K. & van Biljon, J., 2013. Mobile Phones for the Elderly: a design framework. *Proceedings of the 7th International Development Informatics Association Conference, held in Bangkok, Thailand,* pp. 85-102.

Elokla, N., Yoshitsugu, M. & Yasuyuki, H., 2006. *Understanding of the Concept of Universal Design among Overseas and Japanese Institutions and Manufacturers.* Citeseer.

Evans, S. & Minocha, S., 2013. *Accessibility, usability and safety of online environments: the implications for designing e-learning for older people.* University of Nottingham, UK, In: altc2013 Building new cultures of learning, 10-12 September, 2013, University of Nottingham.

Farage, M. A., Miller, K. W., Ajayi, F. & Hutchins, D., 2012. Design principles to accommodate older adults. *Global journal of health science*, 4(2), p. p2.

Findlater, L. Froehlich, J., Fattal, K., Wobbrock, J., & 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. ACM, pp. 343-346.

Fisk, A. D., Rogers W. A., Charness, N., Czaja, S., Sharit, J., 2009. *Designing for older adults: Principles and creative human factors approaches.*CRC press.

Froehlich, J., Wobbrock, J. O. & Kane, S. K., 2007. *Barrier pointing: using physical edges to assist target acquisition on mobile device touch screens.* Proceedings oProceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM. ACM, pp. 19-26.

Fukuda, R., 2008. Usability analysis of home electrical appliances based on eye tracking and physiological data. *Faculty of Environment and Information Studies, Keio University, Fujisawa,* p. 5.

Fukuda, R. & Bubb, H., 2003. Eye tracking study on Web-use: Comparison between younger and elderly users in case of search task with electronic timetable service. *PsychNology Journal,* 1(3), pp. 202-228.

Gao, Y., Bianchi-Berthouze, N. & Meng, H., 2012. What Does Touch Tell Us about Emotions in Touchscreen-Based Gameplay?. *ACM Trans. Human Computer Interacteraction,* December, 19(4), pp. 31:1--31:30.

Gardner, D. G., Discenza, R. & Dukes, R. L., 1993. The measurement of computer attitudes: An empirical comparison of available scales. *Journal of Educational Computing Research,* 9(4), pp. 487-507.

Glascock, A. P. & Feinman, S. L., 1980. A holocultural analysis of old age. Comparative social research, 3(31), pp. 1-332.

Goldberg, J. H. Stimson, M. J., Lewenstein, M., Scott, N., & Wichansky, A.m., 2002. *Eye tracking in web search tasks: design implications.* Proceedings of the 2002 symposium on Eye tracking research & applications. ACM, pp. 51-58.

Goldberg, J. H. & Kotval, X. P., 1999. Computer interface evaluation using eye movements: methods and constructs. *International Journal of Industrial Ergonomics*, 24(6), pp. 631-645.

Gonzalez, R. T., 2012. *10 Limits to Human Perception and How They Shape Your World.* [Online] Available at: http://io9.com/5926643/10-fundamental-limits-to-human-perception----and-how-they-shape-your-world/all *(accessed 27 January 2015).*

Granata, C. et al., Chetouani, M., Tapus, A., Bidaud, P., Dupourque, V., 2010. *Voice and graphical -based interfaces for interaction with a robot dedicated to elderly and people with cognitive disorders.* RO-MAN, 2010 IEEE, pp. 785-790.

Guillaume, L. & Nadine, V., 2010. *Influence of age and interaction complexity on touch screen.* 12th IEEE International Conference on e-Health Networking Applications and Services (Healthcom), 2010, pp. 246-253.

Harwood, R. H., 2001. Visual problems and falls. *Age and ageing,* Volume 30, pp. 13-18.

Hawthorn, D., 2003. *How universal is good design for older users?.* ACM SIGCAPH Computers and the Physically Handicapped, pp. 38-45.

Hurst, A., Hudson, S. E., Mankoff, J. & Trewin, S., 2008. *Automatically detecting pointing performance.* Proceedings of the 13th international conference on Intelligent user interfaces. ACM, pp. 11-19.

ICT, 2013. ICT Facts and Figures in the world. International Telecommunication Union, February. [Online] Available at: http://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2013-e.pdf *(accessed 26 Feberuary 2015).*

Iwase, H. & Murata, A., 2002. *Comparison of mouse performance between young and elderly - basic study for designing mouse proper for elderly.* IEEE International Conference on Systems, Man and Cybernetics, 2002, pp. 246-251.

Jacob, R. J. & Karn, K. S., 2003. Eye tracking in human-computer interaction and usability research: Ready to deliver the promises. *Mind*, 2(3), p. 4.

Josephson, S. & Holmes, M. E., 2002. Attention to repeated images on the World-Wide Web: Another look at scanpath theory. *Behavior Research Methods, Instruments, & Computers,* 34(4), pp. 539-548.

Karam, M. & schraefel, m., 2005. *A taxonomy of gestures in human computer interactions.* University of Southampton.

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, pp. 68-75. [Online] Available at: http://dl.acm.org/citation.cfm?id=1090800 *(accessed 26 Feberuary 2015).*

Kelley, C. L. & Charness, N., 1995. Issues in training older adults to use computers. *Behaviour & Information Technology, 14(2), 107-120.*

Keogh, E. & Ratanamahatana, C. A., 2005. Exact indexing of dynamic time warping. *Knowledge and information systems,* 7(3), pp. 358-386.

Kim, H., Heo, J., Shim, J., Kim, M., Park, So., & Park, Sa.,2007. Contextual Research on Elderly Users' Needs for Developing Universal Design Mobile Phone. Volume 4554, pp. 950-959.

Kobayashi, M. Hiyama, A., Miura, T., Asakawa, C., Hirose, M., & Ifukube, T., 2011. *Elderly user evaluation of mobile touchscreen interactions.* Springer Berlin Heidelberg, Human-Computer Interaction--INTERACT 2011, pp. 83-99.

Laouris, Y., 2009. Web 3D Challenges on the Socialization and Integration of People with Activity Limitations. Volume 5616, pp. 369-374.

Leitão, R. A., 2012. *Creating Mobile Gesture-based Interaction Design Patterns for Older Adults: a study of tap and swipe gestures with Portuguese seniors,* Portugal.

Linghao, Z. & Ying, L., 2010. *On methods of designing smartphone interface.* IEEE International Conference on Software Engineering and Service Sciences (ICSESS), 2010, pp. 584-587.

Loureiro, B. & Rodrigues, R., 2011. *Multi-touch as a Natural User Interface for elders: A survey.* 6th Iberian Conference on Information Systems and Technologies (CISTI), 2011, pp. 1-6.

McConkie, G. W., 1982. EYE MOVEMENTS AND PERCEPTION DURING READING. *UNIVERSITY OF ILLINOISAT URBANA-CHAMPAIGN51 Gerty DriveChampaign, Illinois 61820BOLT,* February, Issue 229, p. 48.

Mesulam, M.-M., 1998. From sensation to cognition.. *Brain,* 121(6), pp. 1013-1052.

Microsoft, 2009. *Application gestures and semantic behavior.* [Online] Available at: https://msdn.microsoft.com/en-us/library/windows/desktop/ms704830(v=vs.85).aspx *(accessed 27 January 2015).*

Minocha, S., 2013. Accessibility, usability and safety of online environments: the implications for designing e-learning for older people. *2013 Faculty of Mathematics, Computing and Technology, The Open University, UK.*

Minocha, S., Hartnett, E., Dunn, K., Evans, S., , T., Middup, C., Murphy, B., & Roberts, D., 2013. *Conducting empirical research with older people.* In: Designing for- and with - vulnerable people, 27 April 2013, Paris, France..

Minocha, S., Tzanidou, E. & Petre, M., 2005. *Applying eye tracking for usability evaluations of e-commerce sites.* workshop on Commercial Uses of Eye tracking'held at the 19th British HCI Group Annual Conference, Napier University, Edinburgh.

Miyoshi, T. & Murata, A., 2001. *Usability of input device using eye tracker on button size, distance between targets and direction of movement.* IEEE International Conference on Systems, Man, and Cybernetics, 2001, pp. 227-232 vol.1.

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. ACM, pp. 1125-1134.

Motti, L. G., Vigouroux, N., & Gorce, P., 2013. *Interaction techniques for older adults using touchscreen devices: a literature review.* 25ème conférence francophone sur l'Interaction Homme-Machine, IHM'13, 2013.

Mui, Y. Q., 2013. This is what wealth looks by age group. *WONKBLOG,* February 26.

Murata, A., Nakamura, H. & Okada, Y., 2002. Comparison of efficiency in key entry among young, middle and elderly age groups - e ffects of aging and character size of a keyboard on work efficiency in an entry task -. Volume 2, pp. 96-101.

Nations, U., 2012. Population Ageing and Development 2012. Department of Economic and Social Affairs, United Nations, New York, NY 10017, USA.

Neisser, U., 1967. *Cognitive psychology.* Appleton-Century-Crofts.

Nettleton, D. & Gonzalez-Caro, C., 2012. *Analysis of User Behavior for Web Search Success Using Eye Tracker Data.* Web Congress (LA-WEB), 2012 Eighth Latin American, pp. 57-63.

Nicolau, H. & Jorge, J., 2012. *Elderly text-entry performance on touchscreens.* Proceedings of the 14th international ACM SIGACCESS conference on Computers and accessibility. ACM, pp. 127-134.

Obrist, M., Bernhaupt, R., Beck, E. & Tscheligi, M., 2007. *Focusing on elderly: an iTV usability evaluation study with eye-tracking.* Interactive TV: a Shared Experience. Springer Berlin Heidelberg, pp. 66-75.

Organization, W. H. & others, 2010. Definition of an older or elderly person. *Health statistics and health information systems.* [Online] Available at: *http://www. who. int/healthinfo/survey/ageingdefnolder/en/index. html (accessed 21 June 2012).*

Persad, U., Langdon, P. & Clarkson, P., 2006. *Inclusive design evaluation and the capability-demand relationship.* Springer London, In Designing accessible technology (pp. 177-188). Springer London, pp. 177-188.

Phiriyapokanon, T., 2011. *Is a big button interface enough for elderly users?,* Computer Engineer-Mälardalen University, Sweden. Master Thesis 2011.

Piper, A. M., Campbell, R. & Hollan, J. D., 2010. *Exploring the accessibility and appeal of surface computing for older adult health care support.* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, pp. 907-916.

Pitt-Catsouphes, M., Matz-Costa, C. & James, J., 2012. Through a Different Looking Glass: The Prism of Age. *Chestnut Hill, MA: Sloan Center on Aging & Work, Boston College.*

Poole, A. & Ball, L. J., 2004. Eye Tracking in Human-Computer Interaction and Usability Research: Current Status and Future Prospects. *Lancaster University, UK.*

Quek, F., McNeill, D., Bryll, R., Duncan, S., Ma, X., Kirbas, C., McCullough, K., & Ansari, R.,2002. Multimodal human discourse: gesture and speech. *ACM Transactions on Computer-Human Interaction (TOCHI),* 9(3), pp. 171-193.

Quigley, C., Andersen, S., Schulze, L., Grunwald, M., & Müller, M., 2010. Feature-selective attention: evidence for a decline in old age. *Neuroscience letters*, 474(1), pp. 5-8.

Quinn, D., Chen, L. & Mulvenna, M., 2011. *Does Age Make a Difference in the Behaviour of Online Social Network Users?.* Internet of Things (iThings/CPSCom), 2011 International Conference on and 4th International Conference on Cyber, Physical and Social Computing, pp. 266-272.

Rayner, K., 1998. Eye movements in reading and information processing: 20 years of research. *Psychological bulletin,* 124(3), p. 372.

Reddy, V. & Chattopadhyay, T., 2014. *Human Activity Recognition from Kinect Captured Data Using Stick Model.* Human-Computer Interaction. Advanced Interaction Modalities and Techniques. Springer International Publishing, pp. 305-315.

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: The Journal of the Human Factors and Ergonomics Society,* 47(2), pp. 271-288.

Ruiz, J., Li, Y. & Lank, E., 2011. *User-defined Motion Gestures for Mobile Interaction.* New York, NY, USA, Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, pp. 197-206.

Schotter, E. R. & Rayner, K., 2013. *Eye movements in reading, Implications for reading subtitles.* Eye tracking in audiovisual translation.

Seçer, I. & Satyen, L., 2013. Training Skills of Divided Attention among Older Adults. *Journal of Articles in Support of the Null Hypothesis,* 9(2).

Srivastava, A., 2014. Apple Inc. (AAPL) iOS vs Google Inc. (GOOG) Android: The Ultimate Winner ?. *Dazeinfo*. [Online] Available at: http://dazeinfo.com/2014/03/24/apple-aapl-ios-vs-googles-goog-android-won/ *(accessed 26 February 2015)*.

SR_Research.Ltd, 2010. *EyeLink? 1000 Installation Guide Tower, Desktop, LCD Arm, Primate, and Long Range Mounts Remote, 2000 Hz and Fiber Optic Camera Upgrades*.

Stockholm, T. E., 2009. The Annual Meeting of the European institute for design and disability in Stockholm. *Annual General Meeting of the European Institute for Design and Disability in Stockholm.*

Stößel, C., 2012. *GESTURAL INTERFACES FOR ELDERLY USERS- HELP OR HINDRANCE?*. Faculty of Sciences, Mechanical Engineering and Transport Systems, The Technical University of Berlin, PhD thesis 2012: The Technical University of Berlin. Faculty of Sciences, Mechanical Engineering and Transport Systems. PhD thesis 2012.

Stößel, C., 2009. *Familiarity As a Factor in Designing Finger Gestures for Elderly Users.* New York, NY, USA, Proceedings of the 11th International Conference on Human-Computer Interaction with Mobile Devices and Services. ACM, pp. 78:1-78:2.

Stößel, C., Wandke, H. & Blessing, L., 2010. *Gestural Interfaces for Elderly Users: Help or Hindrance?*. Springer Berlin Heidelberg, Gesture in Embodied Communication and Human-Computer Interaction, pp. 269-280.

Stößel, C., Wandke, H. & Blessing, L., 2009. An evaluation of finger-gesture interaction on mobile devices for elderly users. *Prospektive Gestaltung von Mensch-Technik-Interaktion*, Volume 8, pp. 470-475.

Sugawara, Y., Sato, M., Sugihara, T. & Kasuga, M., 2004. *Experimental approaches to user friendly audio visual contents for the elderly people.* Yoto, Utsunomiya, Tochigi, Japan, 2004 IEEE Region 10 Conference, TENCON 2004. Japanese Ministry of Education, pp. 391 - 394 Vol. 2.

Sulaiman, S. & Sohaimi, I., 2010. *An investigation to obtain a simple mobile phone interface for older adults.* 2010 International Conference on Intelligent and Advanced Systems (ICIAS), pp. 1-4.

Sultana, A. & Moffatt, K., 2013. Automatic Error Detection from Pointing Device Input Data. [Online] Available at: https://www.asis.org/asist2013/proceedings/submissions/posters/46poster.pdf *(accessed 27 January 2015)*.

Su, Q.-Y. & Li, X.-W., 2010. *Age/Gender/Occupation and Mobile Phone Technology Adoption: A Cross-Cultural Study in China (Beijing) And the UK (Portsmouth).* International Conference on Management and Service Science (MASS), 2010, pp. 1-4.

Takeuchi, T. & Habuchi, Y., 2007. *A Quantitative Method for Analyzing Scan Path Data Obtained by Eye Tracker.* IEEE Symposium on Computational Intelligence and Data Mining, 2007. CIDM 2007., pp. 283-286.

Teather, R. J., Natapov, D. & Jenkin, M., 2010. *Evaluating haptic feedback in virtual environments using ISO 9241--9.* Virtual Reality Conference (VR), 2010 IEEE, pp. 307-308.

Teimourikia, M., Saidinejad, H., Comai, S. & Salice, F., 2014. *Personalized Hand Pose and Gesture Recognition System for the Elderly.* Universal Access in Human-Computer Interaction. Aging and Assistive Environments. Springer International Publishing, pp. 191-202.

Tibken, S. & Dolcourt, J., 2013. Eye-tracking tech in the Samsung Galaxy S4? Say what?. *CNET-Mobile.* [Online] Available at: http://www.cnet.com/news/eye-tracking-tech-in-the-samsung-galaxy-s4-say-what/ *(accessed 27 January 2015)*.

Toyota, Y., Sato, D., Kato, T. & Takagi, H., 2014. *Easy Handheld Training: Interactive Self-learning App for Elderly Smartphone Novices.* Universal Access in Human-Computer Interaction. Aging and Assistive Environments. Springer International Publishing, pp. 203-214.

Tu, H., 2012. *Designing Touch-based Gesture Interactions,* Information Systems Engineering, Kochi University of Technology, German, PhD Thesis.

UN, 2013. world population ageing 2013. *DESA, United Nations, New York (2013)*.

Verstockt, S., Decoo, D., Nieuwenhuyse, D., Pauw, F., & Van de R., 2009. *Assistive smartphone for people with special needs : The Personal Social Assistant.* 2nd Conference on Human System Interactions, 2009. HSI '09, pp. 331-337.

Victor, C. R., 2010. *Ageing, health and care.* The Policy Press.

Wagner, N., Hassanein, K. & Head, M., 2010. Computer use by older adults: A multi-disciplinary review. Computers in Human Behavior, 26(5), pp. 870-882.

Wobbrock, J. O., Morris, M. R. & Wilson, A. D., 2009. *User-defined Gestures for Surface Computing.* New York, NY, USA, Proceedings of the SIGCHI Conference on Human Factors in Computing Systems ACM, pp. 1083-1092.

Yarbzls, A. L., 1967. *Eye movement and vision.* Institute for Problems of Information Transmission Academy of Sciences of the USSR, Moscow.

Zimmermann, K. A., 2014. Procedural Memory: Definition and Examples. *LiveScience Contributor,* February.

Appendices

A. **Eye Tracker Demographic Data Sheet**

A.1 Demographic data:

1. Participant ID: ……………....... Participant Email: ………………………..
2. What is your first language? …………………..
3. Occupation: …………………....... Education Level: …………………..
4. Please tick one of the age group bellow:

Age Brackets	20 – 29	30 - 39	40 – 49	50-59	60 +
✓					

A.2 Mobile phone and Apps experience:

5. How many years have you used a mobile phone? …….
6. How many times per a day do you use a mobile phone for calling? …….
7. Please give details of your current and previous mobile phones in the table below:

	Mobile phone name	Number of Years
Current Phone 1		
Current Phone 2		
Previous Phone 1		
Previous Phone 2		

Choose any of these software do you use with how many years on your mobile phone:

	Software	✓	Number of Years
1	Skype		
2	Tango		
3	Viber		
4	WhatsApp		
5	Yahoo email		
6	Facebook		
7	Other (please specify)		

B. Gestures Demographic Data Sheet

B.1 Demographic data:

1. Participant Email: ……………………………………………………….
2. Occupation: ………………… Education Level: ………………………….
3. DOB (year): ……………….

B.2 Mobile phone and tools experience:

Tick the option that applies to you:

How frequently do you use Phone with touch screen a day please tick your answer:

Up to 2 hours	From 2 up to 4 hours
From 4 hours up to 6 hours	More than 6 hours.
What are you doing during these hours on your mobile: Chatting……….., Texting………, Calling………., Browsing………, Gaming…………, Using maps…………., Other (please specify): ………….……	

Specify your experience in using touch smartphones with different screen sizes:

Months/Years	Finger/Pen Stylus	Yes/No	Screen size
(M)/(Y)			Normal size (ex. Samsung S3 or iphone) (around 4 inch or so)
(M)/(Y)			Medium size (tablets) (around 7 inches or so)
(M)/(Y)			Large size (tablets) (10.1 inches or so)

C. Consent Form

"The Usability of Smartphones and the Applications"

Consent Form

I have received a copy of the study's information document and Ethical Form for this research.

Y / N (please circle as appropriate)

I understand the researcher's work and collecting data regarding my experience, skills, satisfaction in using Smartphone's applications that would serve his study and I am willing to participate in answering questions in an experiment, an interview and fill-in questionnaire.

Y / N (please circle as appropriate)

I give my consent form to use the data excluding presenting my demographic data to identify me in dissemination activities of this research.

I understand that I am able to withdraw from this research at any time.

Y / N (please circle the appropriate)

Participant's email address: ------------------------------

Participant's contact number: ------------------------------

Signed: --------------------------------- Date: -----------------------------------

Researcher's information:

Name: Suleyman Al-Showarah

Email: suleyman.al-showarah@buckingham.ac.uk

D. Demographic data

D.1 Participants on small smartphone

Table 32. Demographic Data for users who were involved in eye-movement on small smartphone.

ID	Age	Skype (smartphone)	Skype (PC)	Facebook (smartphone)	Facebook (PC)	Email (smartphone)	Email (PC)
P1	30	2	3	2	3	2	13
P2	60+	6	6	3	6	0	12
P3	30	0	5	0	4	3	17
P4	20	2	3	2	7	2	15
P5	20	0.16	3	0.08	4	0.16	5
P6	30	2	2	0	2	5	12
P7	20	1	3	1	3	2	3
P8	20	1	1	1	1	2	8
P9	20	1	2	1	3	2	8
P10	20	1	1	2	4	1	4
P11	30	5	5	5	5	5	10
P12	30	2	5	2	4	2	10
P13	20	0	1	0.5	1	0.5	5
P14	20	1	3	1	3	2	10
P15	20	4	10	5	8	6	12
P16	30	0	0	0	1	0	10
P17	20	3	6	2	4	3	10
P18	20	2	4	2	5	2	5
P19	20	0.5	0	0	0	0.5	0
P20	50	0	5	0	2	0	10
P21	50	0	4	0.5	4	0.5	4
P22	50	1	4	0	3	1	28
P23	40	0	0	0	1	0	10
P24	40	1	1	0	1	0.5	12
P25	40	2	4	3	4	3	16
P26	50	0	0.5	2	5	2	8
P27	50	1	2	2	0	2	17
P28	60+	0.5	6	1	5	4	12
P29	60+	0	0	1	4	0	4
P30	60+	0	1	0	3	0	15
P31	60+	0	2	0	1	0	12
P32	60+	0	1	0	1	0	12
P33	60+	0	0	0	0	0.5	12

P34	60+	0.5	0	1	10	0.5	10
P35	60+	1	1	0	0.5	0.5	12

D.2 Participants on mini-tablet size

Table 33. Demographic Data for users who were involved in eye-movement on mini-tablet.

ID	Age	Skype (smartphone)	Skype (PC)	Facebook (smartphone)	Facebook (PC)	Email (smartphone)	Email (PC)
P36	30	3	5	3	4	3	11
P37	30	1	4	3	4	2	10
P38	30	1	6	1	1	4	10
P39	30	1	2	1	4	1	14
P40	20	2	6	2	7	4	9
P41	20	2	4	0	1	3	6
P42	30	0	0	0	0	0	10
P43	20	0	4	4	6	4	10
P44	30	1	7	3	5	3	12
P45	20	1	2	2	7	3	10
P46	20	3	5	5	7	5	10
P47	30	0	1	0	1	0.5	10
P48	30	0	3	2	6	2	10
P49	20	1	0	3	4	3	9
P50	20	0	5	3	6	3	16
P51	40	0	0	1	1	2	15
P52	50	0	0	0	0	0	10
P53	50	0	2	0	2	0.5	15
P54	50	0	5	0	0	2	15
P55	40	0	3	0	0	0	6
P56	40	0	3	2	7	4	24
P57	40	0	0	3	8	2	25
P58	50	0	0	0	0	0	0.125
P59	50	0.25	0	0	0	0	25
P60	40	2	7	0	0	2	13
P61	50	0	1	0	0	0	7
P62	50	0	0	0	0	3	17
P63	50	0	0	0	2	0	15
P64	50	0	0	0	0	0	5
P65	60	0	0	0	0	0	5
P66	60	1	1	0	0	0.25	5
P67	60	0	3	0	4	0	15
P68	60	0	1	0	3	0	20

P69	60	3	2	3	6	0	18
P70	60	0	0	0	0	1	15
P71	60	0	0	0	0	1	15

D.3 Participants on large tablet size

Table 34. Demographic Data for users who were involved in eye-movement on large tablet.

ID	Age	Skype (smartphone)	Skype (PC)	Facebook (smartphone)	Facebook (PC)	Email (smartphone)	Email (PC)
P72	30	0.41	8	0.75	3	0.75	12
P73	30	1	4	1	3	2	11
P74	30	3	5	3	3	3	11
P75	20	0	3	2	3	3	12
P76	20	1	2	3	3	2	3
P77	20	0	0	0	0	0	5
P78	20	1	2	3	3	3	4
P79	20	3	7	3	6	2	13
P80	20	0.5	0.5	0	2	1.5	12
P81	30	0	1	0	2	0.33	10
P82	20	1	1	3	3	3	3
P83	30	1	1	1	3	1	14
P84	30	1	2	1	3	3	11
P85	30	0	0	4	4	6	10
P86	20	1	2	1	4	1	5
P87	20	1	1	1	1	1	7
P88	20	0.3	2	0.3	2	0.3	13
P89	50	0	0	0	0	0	10
P90	40	6	6	6	6	5	12
P91	50	0	0	0	0	2	25
P92	40	0	0	1	5	0	22
P93	40	0	3	0.5	2	0.5	8
P94	50	0.5	0	0.5	0	1	15
P95	40	0.25	3	0.25	3	2	13
P96	50	0	1	0	0	0	7
P97	50	0.5	0	0	0	0.5	4
P98	60	0.16	3	0	3	0.16	15
P99	60	1	4	0	0	2	20
P100	60	0	0	0	3	0.5	5
P101	60	0	0.5	0	0	0	3
P102	60	0	3	0	4	0	15
P103	60	0	1	0	1	0	12

D.4 Participants on all two screen sizes of smartphone (touch-gestures)

Table 35. Demographic Data for users who were involved in touch-gestures on two sizes of smartphones.

Small smartphone (60+ years old)								
ID	DOB (year)	Ring Size	Ring Size (MM)	finger length mm	hand span mm	4inch	7inch	10.1inch
P1	1952	R	58.9	65	80	4	0	2
P2	1948	5	73.5	95	85	3	0	0
P3	1950	S	60.2	-	-	0	0	0
P4	1947	R	58.9	75	80	1	0	0
P5	1947	T	61.4	75	80	0	0	0
P6	1949	T	61.4	-	-	0	0	0
P7	1951	K	50	65	79	2.5	0	0
P8	1949	Z	68.5	-	-	0	0	0
P9	1944		75	67	81	0	0	3
P10	1951	u	62.7	70	78	0.5	0	0
P11	1951	A	37.8	70	80	3	0	2
P12	1952	s	60.2	80	80	0	0	0
P13	1953	w	65.3	65	90	0	0	0
Small smartphone (20-39)								
ID	DOB	Ring Size	Ring Size (MM)	finger length mm	hand span mm	4inch	7inch	10.1inch
P14	1980	T	61.4	75	85	5	0	3
P15	1987	O	55.1	70	75	4	0	1
P16	1986	-	-	-	-	3	3	0
P17	sara	R	58.9	-	-	0	0	0
P18	1979	Q	57.6	-	-	3	0	0
P19	1992	Q	57.6	-	-	3	0	0.25
P20	1992	R	58.9	-	-	0.75	0.16	0
P21	1988	W	65.3	-	-	1	0	0
P22	1994	S	60.2	-	-	2	0	0
P23	1985	L	51.2	80	70	1	1	0
P24	1987	U	62.7	85	90	2	0	0
P25	1975	-	-	-	-	0.5	0	1
P26	1989	-	-	-	-	2	0	2
mini-tablet (60+ years old)								
ID	DOB (year)	Ring Size	Ring Size (mm)	finger length cm	hand span cm	4inch	7inch	10.1inch

P27	1953	W	65.3	-	-	5	0	2
P28	1945	R	58.9	-	-	5	0	2
P29	1945	U	62.7	-	-	0.5	0	2
P30	1946	-	-	-	-	0	0	2
P31	1952	X	66.6	78	78	2	0	0
P32	1941		75	65	90	0.041	0	2
P33	1946	s	60.2	90	80	0	0	0.6
P34	1953	5	73.5	80	85	0	0	0
P35	1950	R	58.9	75	85	2	0	0
P36	1942	5	73.5	75	85	0	0	0.5
P37	1941	y	67.8	70	70	0	0	0
P38	1949	w	65.3	85	75	2	1	0
mini-tablet (20-39 years old)								
ID	DOB (year)	Ring Size (mm)	finger length cm	hand span cm	age	4inch	7inch	10.1inch
P39	1993	-	-	-	20	3	1	1
P40	1986	65.3	-	-	27	4	1	0.92
P41	1987	53.8	-	-	26	0	0	2.33
P42	1987	58.9	70	75	26	3.25	0	0.5
P43	1985	58.9	-	-	28	1.5	0	0
P44	1992	56.3	-	-	21	0.66	1.33	0
P45	1977	73.5	80	90	36	0	0	1
P46	1994	60	72	79	19	4	0.08	0
P47	1991	55.1	-	-	22	0	0.33	1
P48	1985	62.7	-	-	28	3	0	0
P49	1982	64	-	-	31	1	0	0
P50	1985	64	75	95	28	5.25	0	3.6

E. Smartphone applications (Stimulus: Eye Movement)

E.1 Medium screen size – mini-tablet size

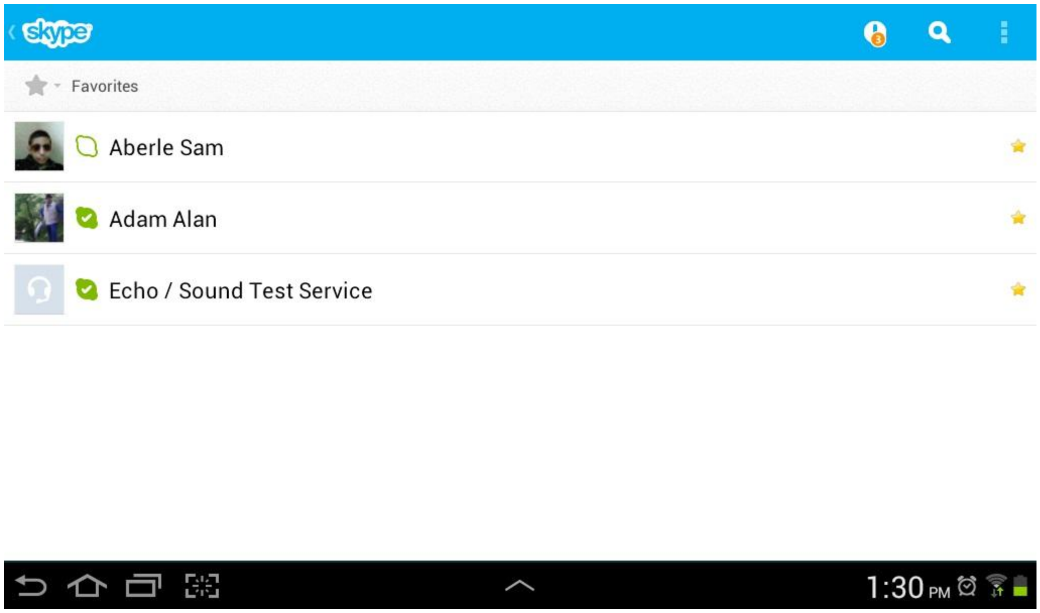


Figure 31. Skype Contact list.

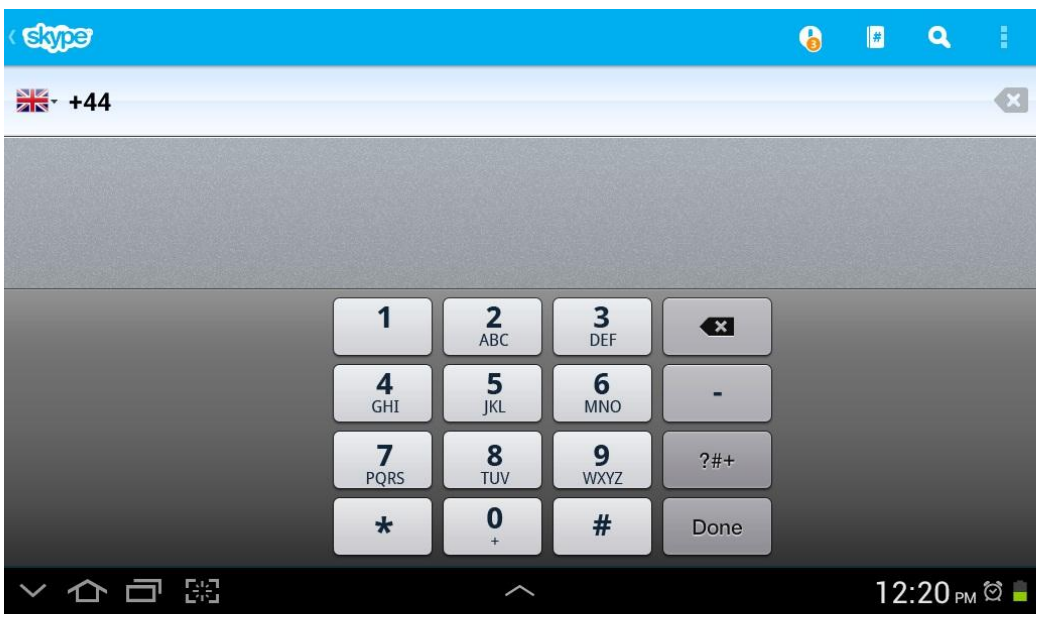


Figure 32. Skype Calling Screen.

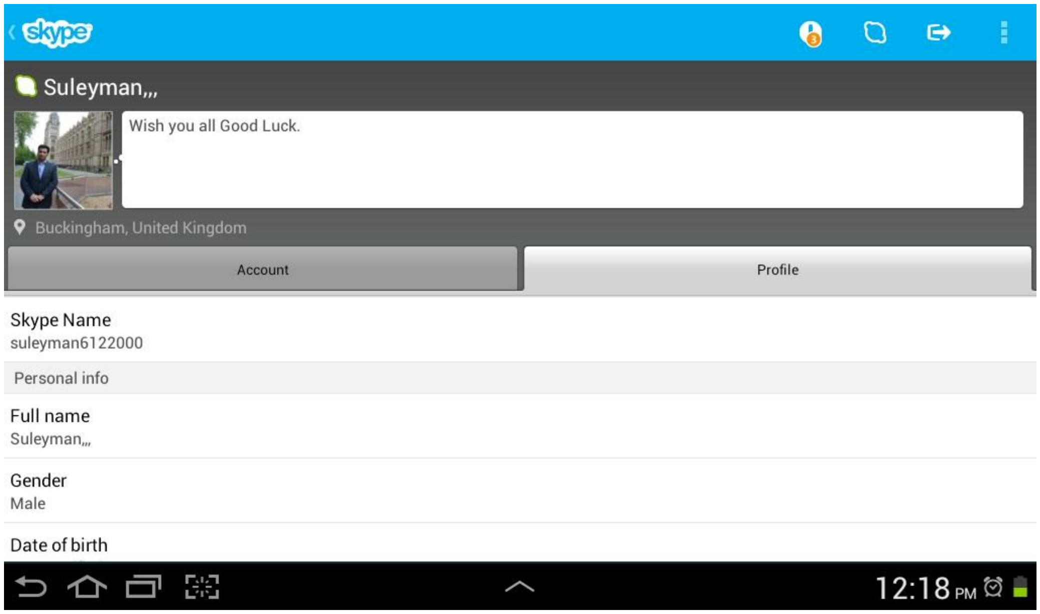


Figure 33. Skype account holder profile.

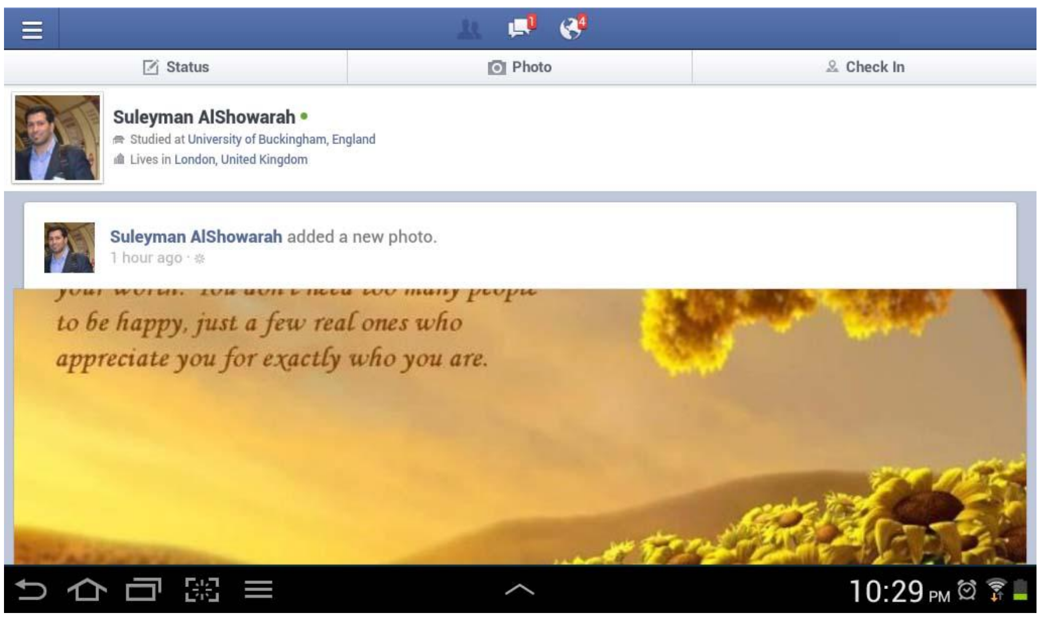


Figure 34. Facebook main screen

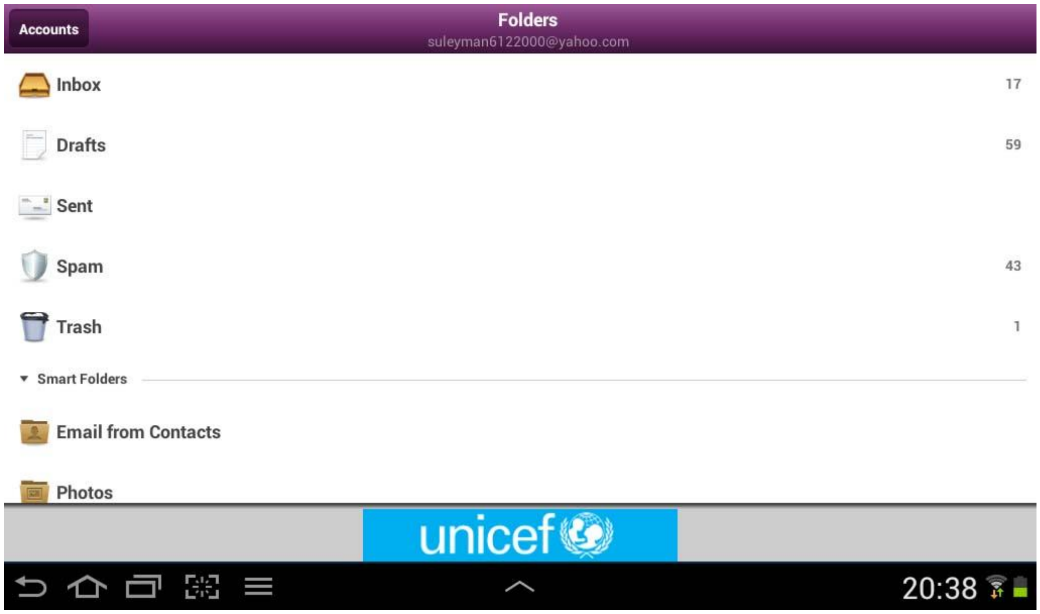


Figure 35. Yahoo mail screen.

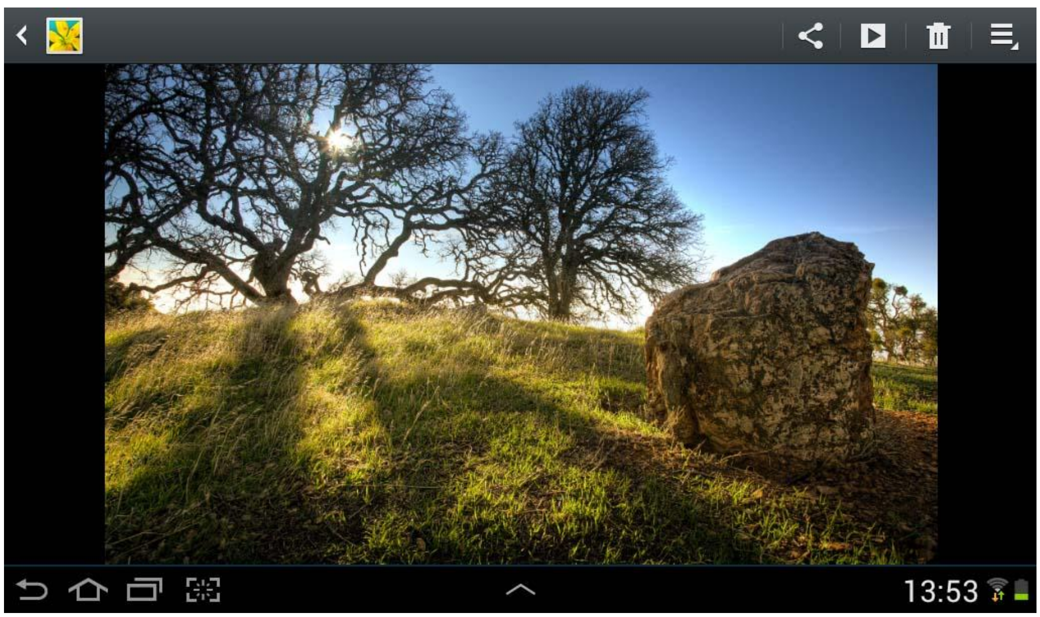


Figure 36. Tablet Gallery screen.

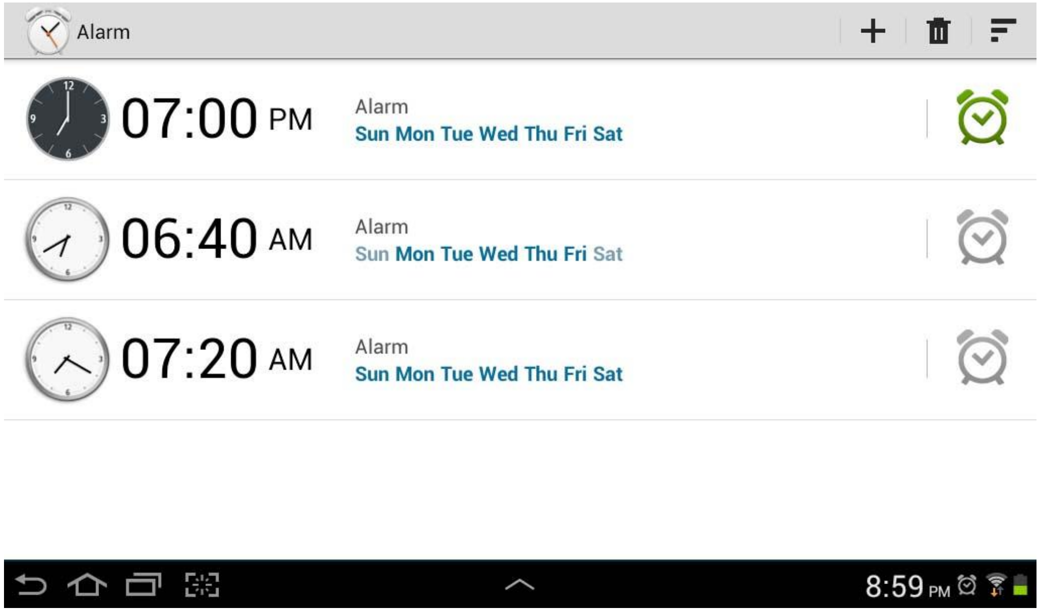


Figure 37. Tablet alarm screen.

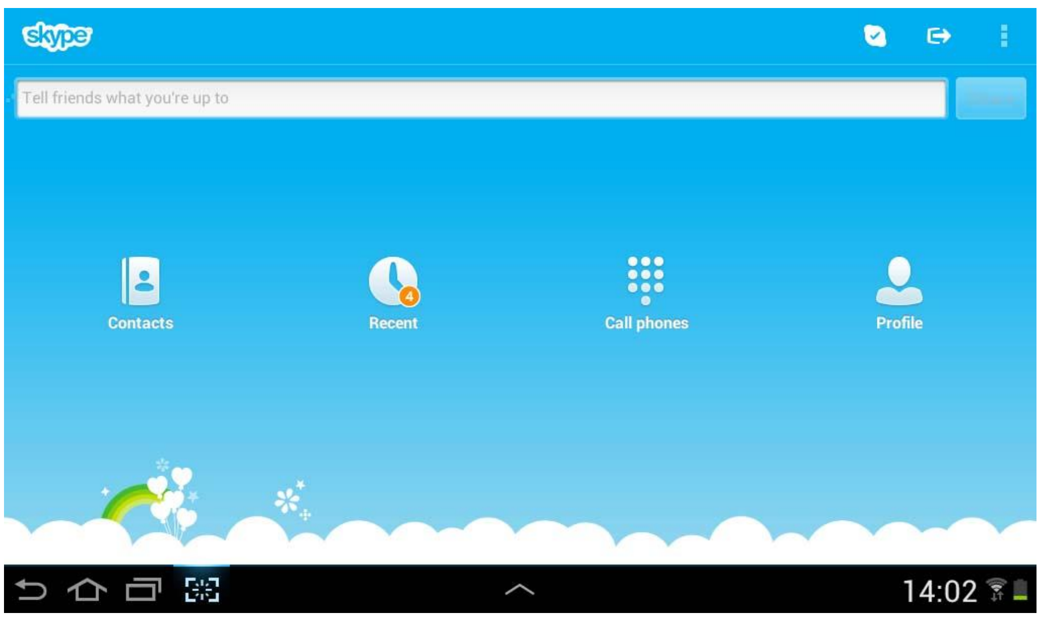


Figure 38. Skype main screen.

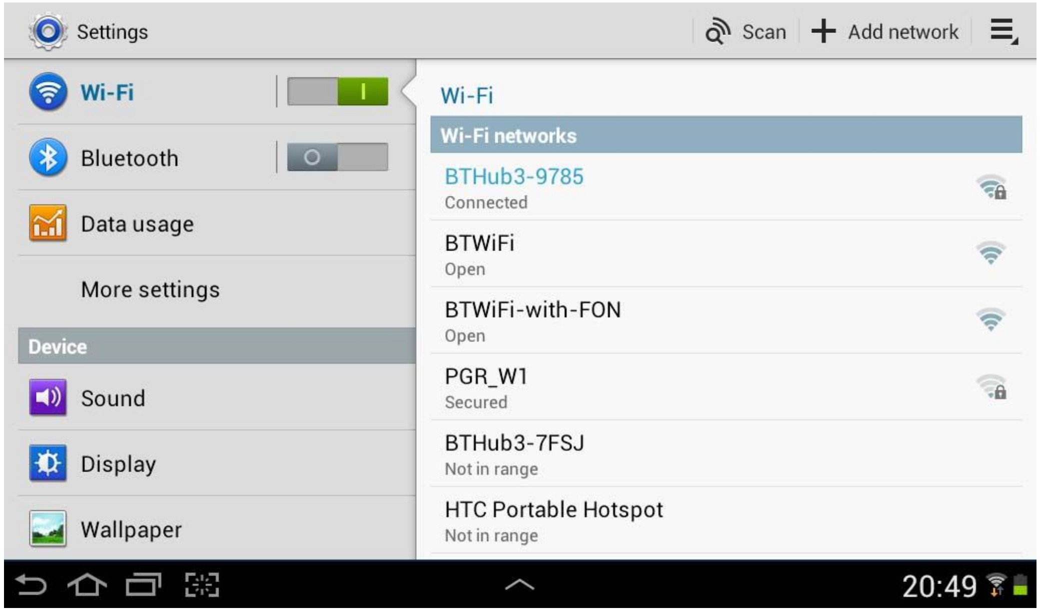


Figure 39. Tablet setting screen.

D.2 Large screen size – 10.1 tablet size

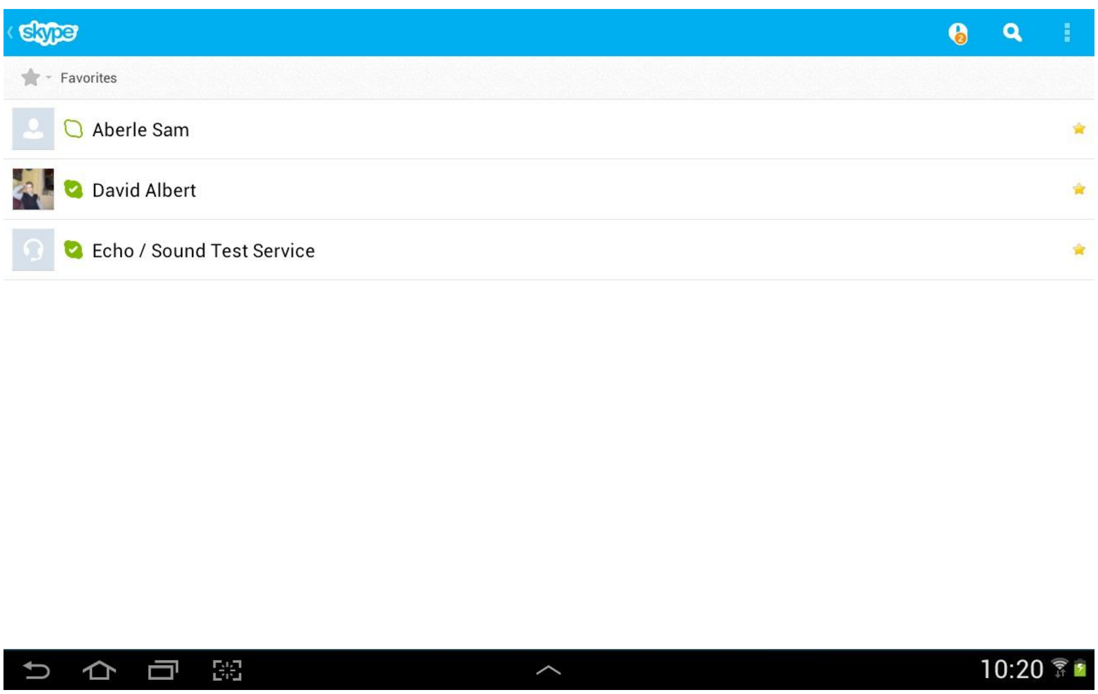


Figure 40. Skype contact list.

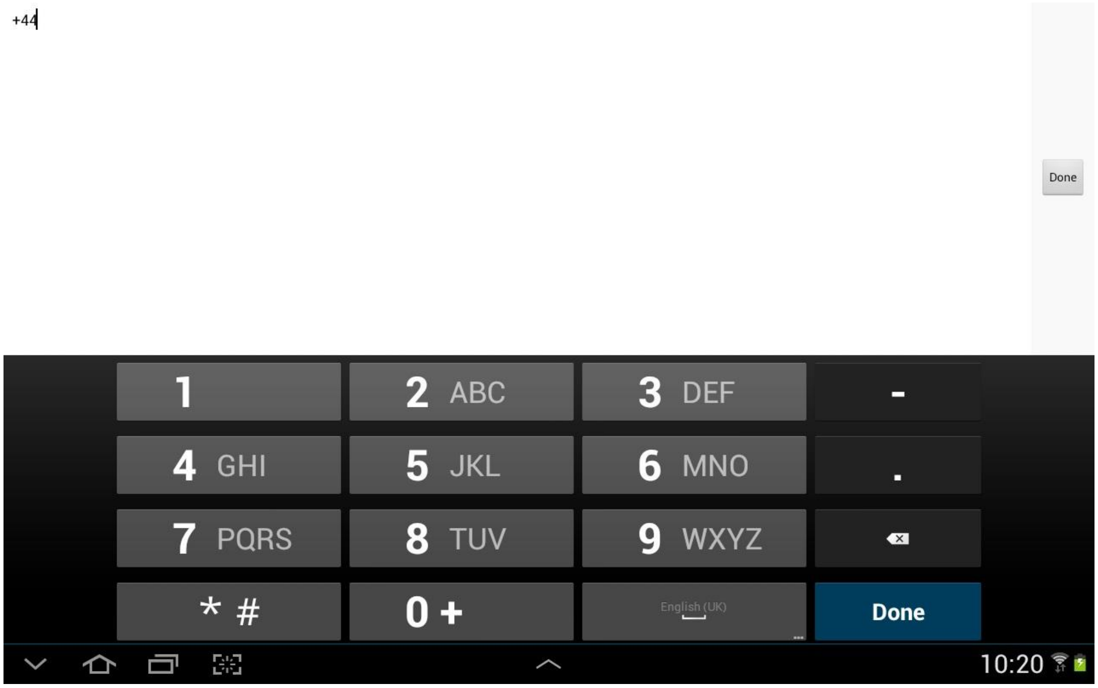


Figure 41. Tablet calling screen.

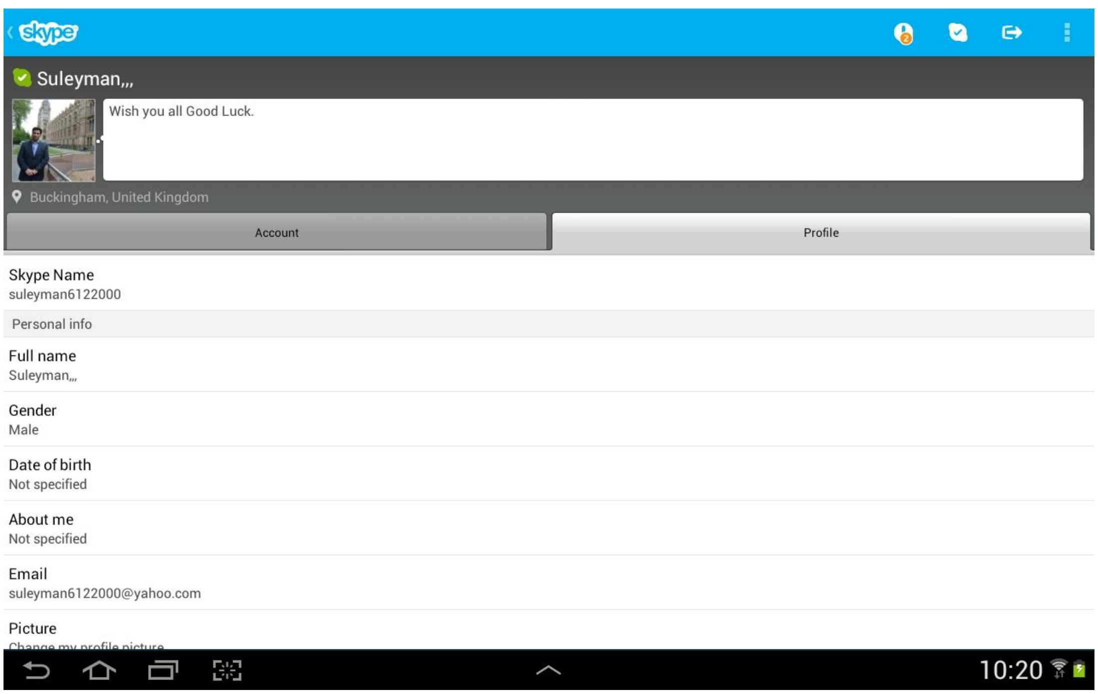


Figure 42. Skype account holder profile.

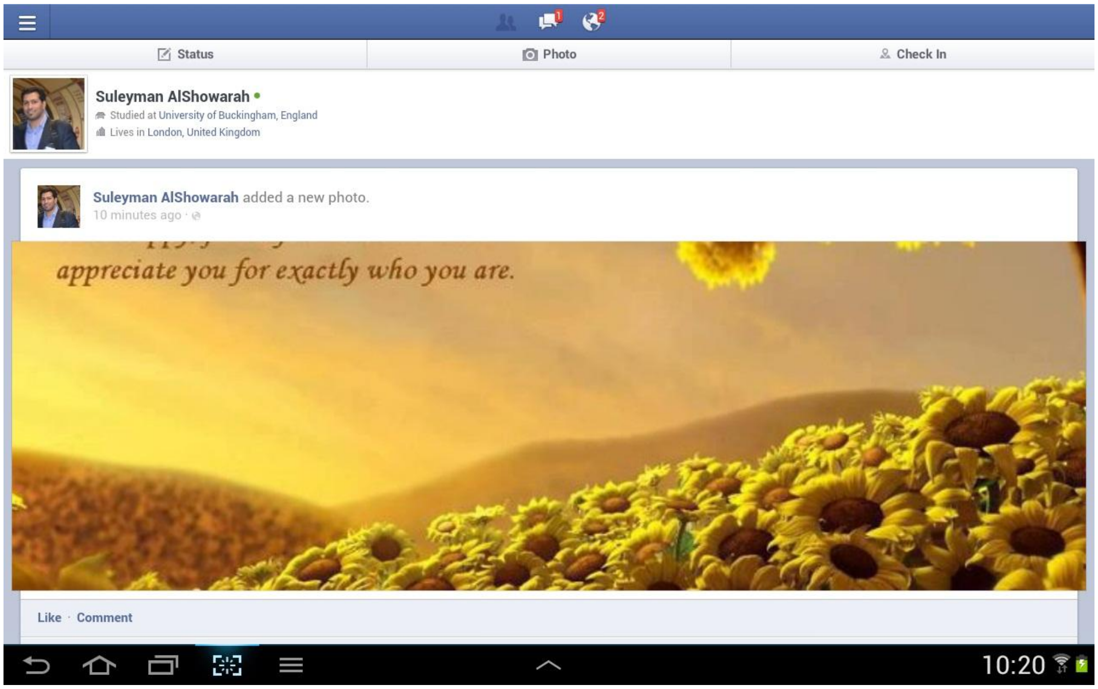


Figure 43. Facebook main screen.

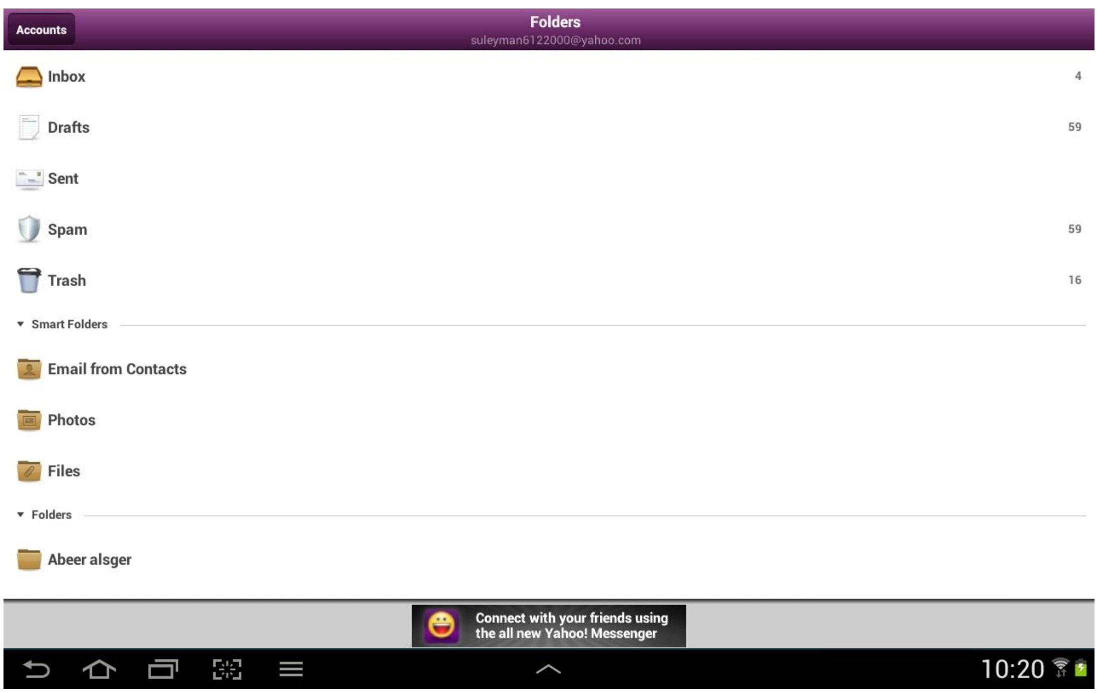


Figure 44. Yahoo email screen.

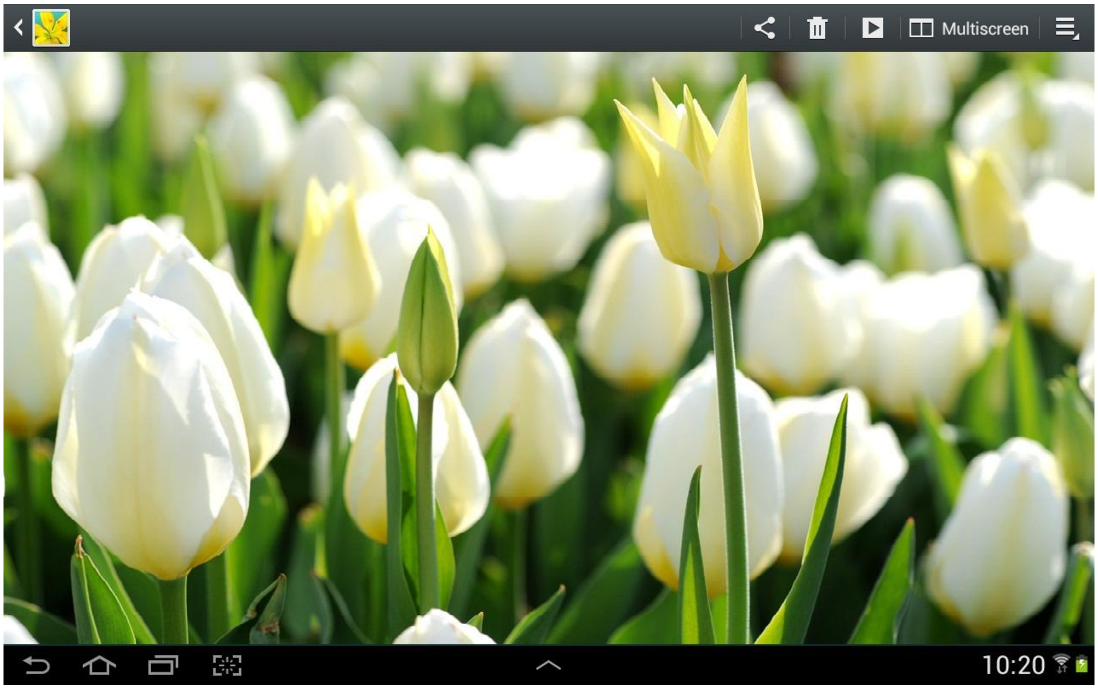


Figure 45. Tablet gallery screen.

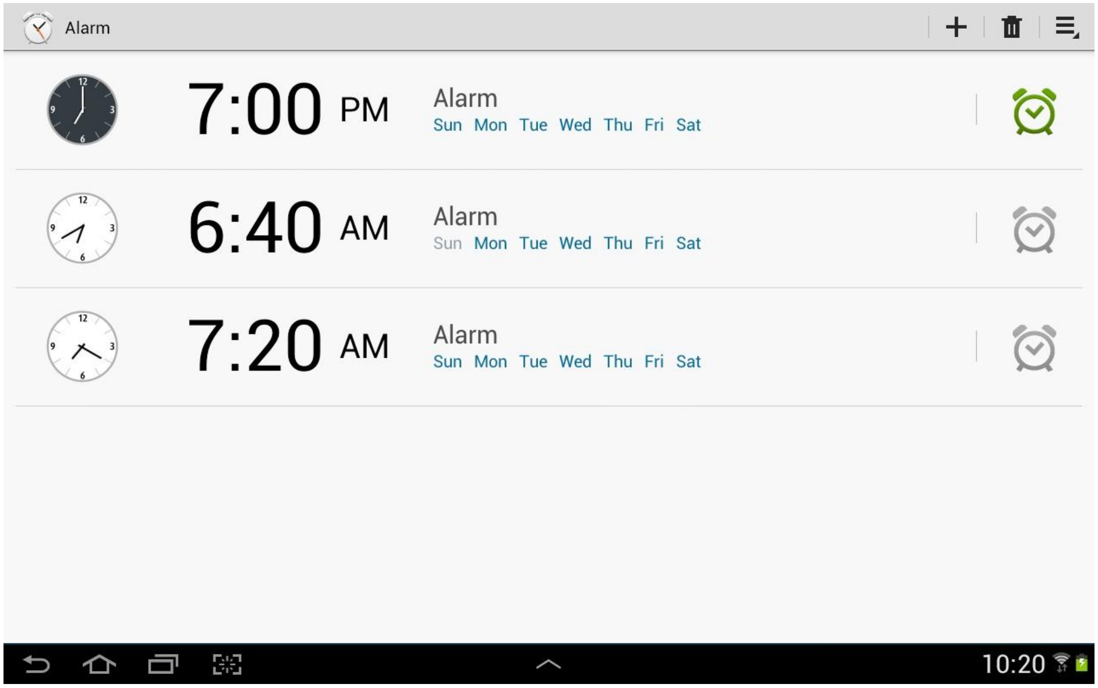


Figure 46. Tablet alarm screen.

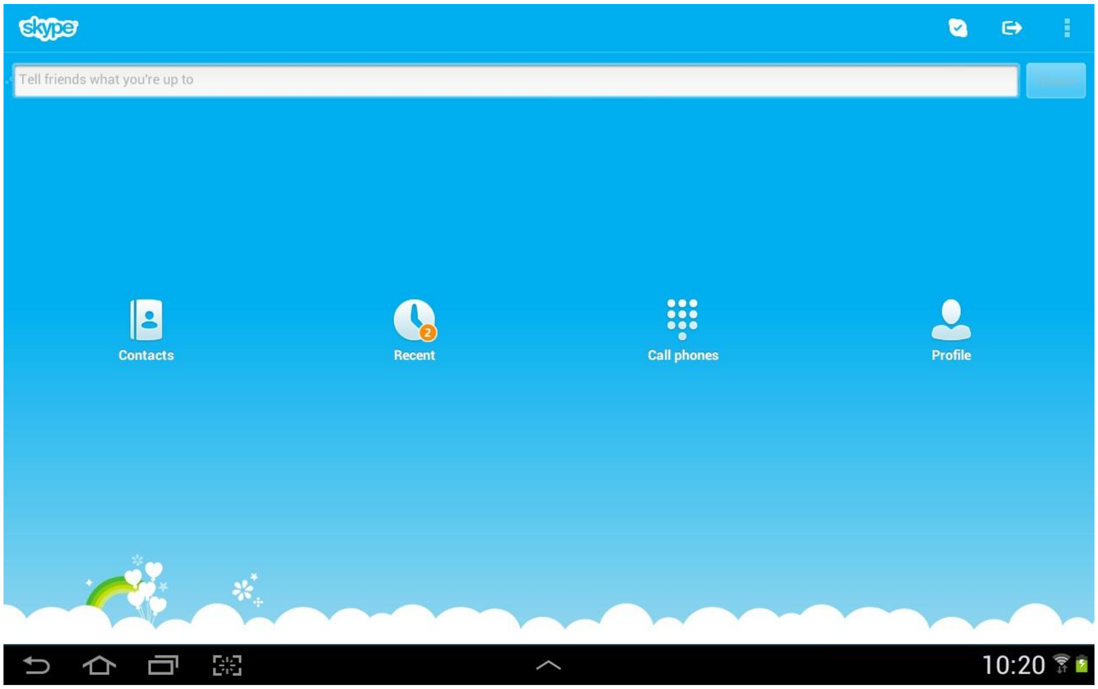


Figure 47. Skype main screen.

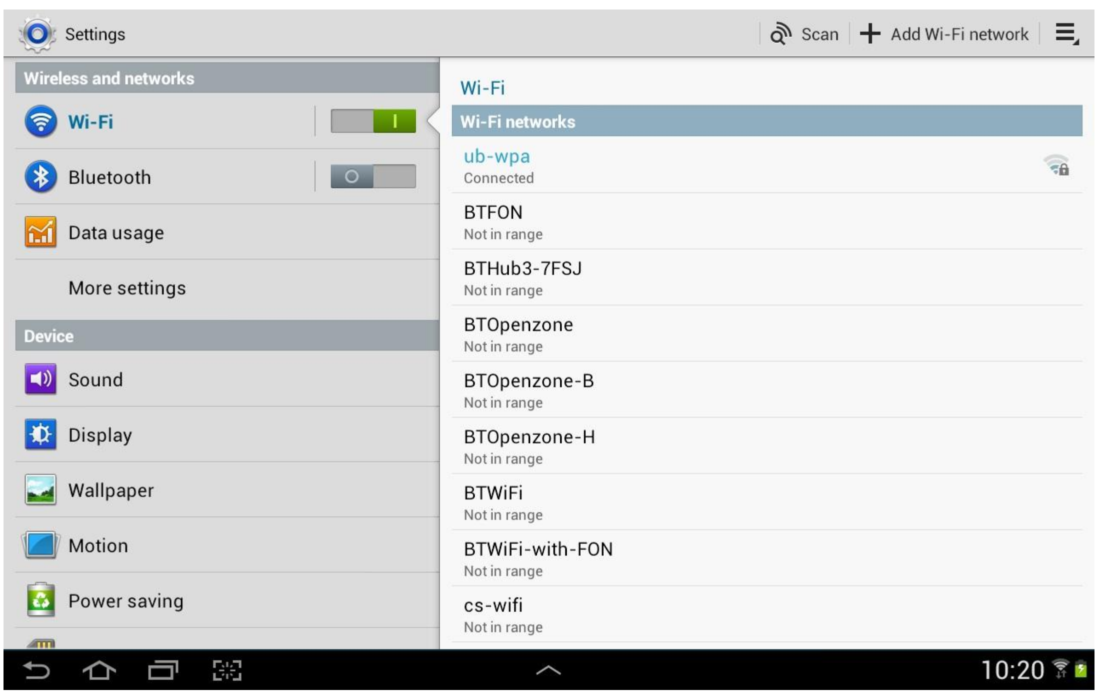


Figure 48. Tablet setting screen.

F. Finger Measurements for Gesture Experience

Table 36. Finger measurements for gestures experiments.

		Participant No	Finger tip Size (mm)	Finger base Circumferences Size (British size)	Finger base Circumferences Size (mm)	Finger length (mm)	Hand span (mm)
Small Smartphone	EG	**P1**	15	R	58.9	65	80
		P2	-	5	73.5	95	85
		P3	-	S	60.2	-	-
		P4	-	R	58.9	75	80
		P5	-	T	61.4	75	80
		P6	-	T	61.4	-	-
		P7	-	K	50	65	79
		P8	-	Z	68.5	-	-
		P9	18	-	75	67	81
		P10	15	U	62.7	70	78
		P11	-	A	37.8	70	80
		P12	-	S	60.2	80	80
		P13	-	W	65.3	65	90
	YG	**P14**	-	T	61.4	75	85
		P15	-	O	55.1	70	75
		P16	-	-	-	-	-
		P17	-	R	58.9	-	-
		P18	-	Q	57.6	-	-
		P19	-	Q	57.6	-	-
		P20	-	R	58.9	-	-
		P21	-	W	65.3	-	-
		P22	-	S	60.2	-	-
		P23	21	L	51.2	80	70
		P24	22	U	62.7	85	90
		P25	-	-	-	-	-
		P26	-	-	-	-	-
mini-tablet	EG	**P27**	-	W	65.3	-	-
		p28	-	R	58.9	-	-
		P29	-	U	62.7	-	-
		P30	-	-	-	-	-
		P31	25	X	66.6	78	78
		P32	23	-	75	65	90
		P33	-	S	60.2	90	80
		P34	15	5	73.5	85	85

		P35	25	R	58.9	75	85
		P36	-	5	73.5	75	85
		P37	-	Y	67.8	70	70
		P38	-	W	65.3	85	75
	YG	**P39**	-	-	-	-	-
		P40	-	W	65.3	-	-
		P41	-	N	53.8	-	-
		P42	15.5	R	58.5	70	75
		P43	-	R	58.9	-	-
		P44	-	P	56.3	-	-
		P45	20	5	73.5	95	90
		P46	-	-	60	72	79
		P47	-	O	55.1	-	-
		P48	-	U	62.7	-	-
		P49	-	V	64	-	-
		P50	-	V	64	75	95

Table 37. Finger Ring size analysis using Gesture accuracy.

Finger size	**37.5**	**50**	**51.2**	**53.8**	**55.1**	**56.3**	**57.6**	**58.9**	**60.2**	**61.4**	**62.7**	**64**	**65.3**	**66.6**	**67.8**	**68.5**	**73.5**
	A	**K**	**L**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**	**z+5**
EG_smaLL	0.83	0.66						0.32	0.58	0.58	1		0.68			0.74	0.32
NO of participants	1	1						1	2	2	1		1			1	1
AVERAGE	0.75 ↑						0.61					0.58 ↓					
YG_smaLL			0.32		0.25		0.18	0.25	0.3	0.28	0.22		0.15				
NO of participants			1		1		2	2	1	1	1		1				
AVERAGE	0.29 ↑						0.26					0.15 ↓					
EG_mini-tablet								0.07	0.27		0.12		0.03	0.07	0.12		0.29
NO of participants								2	1		1		2	1	1		2
AVERAGE	0 ↓						0.13					0.14 ↑					
YG_mini-tablet				0.09	0.02	0.06		0.07			0.03	0.05	0.04				0.03
NO of participants				1	1	1		2			1	2	1				1
AVERAGE	0.06 ↑						0.06 ↑					0.04 ↓					
ALL AVG	**0.36** ↑						**0.26**					**0.23** ↓					

Table 38. Finger Ring size analysis using FP.

Finger size	37.5	50	51.2	53.8	55.1	56.3	57.6	58.9	60.2	61.4	62.7	64	65.3	66.6	67.8	68.5	73.5
	A	**K**	**L**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**	**z+5**
EG_smaLL	0.42	0.34						0.5	0.41	0.41	1		0.42			0.35	0.52
NO of participants	1	1						1	2	2	1		1			1	1
AVERAGE	0.38 ↓						0.46					0.43 ↑					
YG_smaLL			0.45		0.38		0.35	0.35	0.42	0.38	0.39		0.34				
NO of participants			1		1		2	2	1	1	1		1				
AVERAGE	0.42 ↑						0.38					0.34 ↓					
EG_mini-tablet								0.17	0.18		0.21		0.17	0.19	0.27		0.27
NO of participants								2	1		1		2	1	1		2
AVERAGE	0 ↓						0.18					0.22 ↑					
YG_mini-tablet				0.19	0.14	0.16		0.17			0.17	0.16	0.23				0.18
NO of participants				1	1	1		2			1	2	1				1
AVERAGE	0.16 ↓						0.17					0.18 ↑					
ALL AVG	**0.32 ↑**						**0.30**					**0.29 ↓**					

Table 39. Finger Ring size analysis using Speed.

Finger size	37.5	50	51.2	53.8	55.1	56.3	57.6	58.9	60.2	61.4	62.7	64	65.3	66.6	67.8	68.5	73.5
	A	**K**	**L**	**N**	**O**	**P**	**Q**	**R**	**S**	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**	**z+5**
EG_smaLL	293.6	310						477.64	476.26	476.26	1		215.7			352.3	532.22
NO of participants	1	1						1	2	2	1		1			1	1
AVERAGE	301.77 ↓						400.83					366.72 ↑					
YG_smaLL			619.3		963.8		787	509.87	754.01	559.39	660.3		637.7				
NO of participants			1		1			2	1	1	1		1				
AVERAGE	791.54 ↑						598.682					637.67 ↓					
EG_mini-tablet								505.76	1002.5		366.8		548.4	750.3	753		327.62
NO of participants								2	1		1		2	1	1		2
AVERAGE	0 ↓						595.195					542.57 ↑					
YG_mini-tablet				402.5	633.3	609.7		482.91			841.7	670.6	433.1				910.48
NO of participants				1	1	1		2			1	2	1				1
AVERAGE	548.53 ↓						602.51					671.19 ↑					
ALL AVG	**547.28 ↓**						**549.30**					**554.54 ↑**					