IMPROVING MOBILE DEVICES USER INTERFACE NAVIGATION FOR ELDERLY USING PREDICTIVE - ASSISTIVE TECHNOLOGY APPROACH

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other University.

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DEDICATION

I dedicate this thesis to my dear husband Arthur and our adorable children Ian and Shiku for your love and support; am humbled.

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ABBREVIATIONS

Apps	Applications
AMPS	Assessment of Motor and Process Skills
AT	Assistive Technology
AUI	Adaptive User Interfaces
GUI	Graphical User Interface
IMP	Intelligent Mobility Platform
iOS	Lion X Operating System
HAAT	Human Activity Assistive Technology Model
POTS	Plain Old Telephone System
SDAZ	Speed-Dependent Automatic Zooming
UI	User Interface

ABSTRACT

The mobile technology being one of the fastest growing industrial sectors ever, mobile devices use is a phenomenon that has crossed all age and gender boundaries globally. Mobile applications have blossomed in popularity and ubiquity, with each generation, the multitude and diversity of applications continues to grow. Increasingly large number of the applications installed on smartphones tends to slow the application access efficiency. The results of a study carried out on elderly and mobile devices interactions indicates that users with declining abilities as a result of aging find it difficult to navigate the complex structure of the modern mobile devices interface. Support that can improve daily application interaction experience is poised to be widely beneficial. This research has realized an intelligent application predictor, which predicts the applications that are most likely to be accessed by the user; prediction is based on Naïve Bayesian model leveraging the application accessed properties such as frequency of access, time of access, the health and economic benefit of the application. An evaluation study involving six elderly users was carried out where the predictor was installed in their mobile devices for six weeks, a survey based on three aspects: interface presentation, navigation experience and overall satisfaction. All respondents rated application predictor high in aiding users and saving them on memory trying to recall applications, the users reported increase in efficiency when using the predictor compared to the interaction with the standard user interface (UI).

CHAPTER ONE

INTRODUCTION

1.1 Background

The mobile technology being one of the fastest growing industrial sectors ever, mobile devices use is a phenomenon that has crossed all age and gender boundaries globally. Mobile phones not only evolved with regard to technology, they also became ubiquitous and pervasive in people's daily lives by becoming capable of supporting them in various tasks (Böhmer, 2013). The elderly are living longer and are more active, and are very interested in the use of technology as communication tool to stay informed (Nielsen, 2002). The future points to the use of technology to help the elderly people maintain their independence even if they develop age-related barriers, particularly in the use of technology. Thus the elderly should not be neglected in the design of mobile devices (Kurniawan, 2007). In modern structure, most applications are hidden and users are required to navigate through a series of screens.

As the development of mobile devices advances, the increased functionality is providing interfaces with numerous iconified applications (apps) to the users. Mobile apps have blossomed in popularity and ubiquity. With each generation, the multitude and diversity of apps continues to grow. A recent tally revealed 380,000 iOS apps, 250,000 Android apps and 35,000 Windows Phone (WP) apps. With so many apps out there, systems support that can improve our daily app interaction experience is poised to be widely beneficial (Yan, 2012). Little support exists for end-users to make effective and efficient use of their smartphones given the huge numbers of applications that are available (Leiva, Böhmer, Gehring, & Krüger, 2012). It is not easy to present the entire list of applications on the screen of a phone because they usually outnumber the lines on the screen (Tang, 2005). Therefore, some applications are hidden, and the users must navigate through a series of screens to find a service. This demands users to memorize the function names and their relative location within the device (Ziefle, Arning, & Bay, 2006). When people grow older, cumulative effects of several diminishing capacities are most likely to result into a situation the elderly person cannot meet the imposed cognitive demands presented by an environment that has been designed for the young (Freudenthal, 2005). The diminishing capacities (i.e. cognitive process, motor functions and spatial abilities) are all important factors in usability (Ziefle & Bay, 2005).

Elderly people are considered as non-technological, but they accept technology as long as it helps their needs; however they always keep some distance and never totally accept it in the same way as young people do (Conci, Pianesi, & Zancanaro, 2009). Elderly report fear of damaging current technical products in case of misuse (Goebel, 2007). This prevents them from exploring technical products by trialing which is mostly done by other users. The bottom-line is to help users to access applications on the mobile device with attempt to improve the efficiency of mobile interface navigation.

1.2 Problem Statement

Mobile devices design provides interfaces with pool of icons representing the applications to be used by the users. Presenting all the applications on the screen of the device is not easy because they usually outnumber the lines on the screen (Tang, 2005). However, a decrease in size and an increase in functionality lead to an increase in complexity of the device. This is a problem, not only for persons who lack an interest for or are unaccustomed to technology, but also for persons who have decline in cognitive ability because a lot of memory work load is required in order to be able to navigate through the different applications of such a device (Goebel, 2007). A study by (Tang & Peng, 2006) showed that, older users actually face a more complex problem in terms of figuring out how mobile applications are structured.

Mobile devices are acquired by a widespread population of users who do not probably receive any formal training in operating them (Dunlop & Brewster, 2010). Furthermore, device vendors consolidate multiple functions into a single device and the mobile user has to handle interleaving of multiple activities previously unknown when only a landline or a stationary computer was used (Preece & Rogers, 2002). Social isolation and diminished access to productive (predominantly younger) mobile phone users together with the mental effects of aging justify the need to assist older adults in mobile device applications lookup.

1.3 Proposed solution

This study carefully enhanced the previous research pertaining to mobile devices navigation to assist the elderly users. It entailed improving navigation to mobile applications using an intelligent application predictor, which predicts the application that are most likely to be accessed by the user, prediction is based on classification of the accessed app properties such as frequency of access, time of access, the health and economic benefit of the app as specified by the users using a Naïve Bayesian model. By presenting the applications predictor with an adaptable user interface to elderly users with cognitive decline ensures reduced memory load resulting to ease of use for the mobile devices, and this was fundamental in this practical contribution

1.4 Objectives of the Research

1.4.1 Broad Objective

To improve mobile devices user interface navigation trends and experience by the elderly people and propose a prediction assistive technology to improve navigation and ease of use of mobile devices.

1.4.2 Specific Objectives

1. To find out the kind of navigational encounters faced by elderly users with declining cognitive abilities when accessing applications on mobile devices.

2. To identify older adults requirements when interacting with mobile devices user interface applications.

3. To develop an intelligent application predictor which predicts applications that are most likely to be accessed by the users.

4. Present the UI in a reorganized user specified layout to enable elderly performs their intended navigation more efficiently.

1.5 Overview of the Chapters

Chapter 1 gives the background to the study, states the problem statement, and gives a highlight on the proposed solution to the problem and the study objectives.

Chapter 2 presents an overview of the existing literature found in the area of study; the review covers a number of studies on Cognitive Load Theory and User Interface Design ,mobile device navigation, adaptive interfaces, Naïve Bayes prediction model and prediction in android with focus in small devices, user interfaces, measuring instruments, the elderly, and usability and the elderly. This chapter prepares the variables and constructs used in the study.

Chapter 3 describes the research framework and approach used to carry out this study, including constructs and variables used to measure aspects for the elderly users of small devices.

Chapter 4 presents the analysis results indicating the navigational challenges, length of using mobile devices and age limitations experienced by the elderly.

Chapter 5 describes the flow of the system design process, prototyping and parameters to actualize the final prototype. The chapter also describes how the various features have been extracted to facilitate the prediction.

Chapter 6 describes the implementation and evaluation of the final application giving the system requirements, the development environment, application prediction and evaluation of the final prototype.

Chapter 7 presents the conclusion, recommendations of this study and highlights areas for further research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

According to the Kenyan population statistics by (NCAPD) there has been dramatic rise in the population of the elderly aged 45 years and above to reach about 2.6 million in 2009. Table 2.1 shows the indicators of population in terms of population size in Millions and population growth rate in percentage against the time interval of 10years since 1969 to 2009 annual growth rate of about 4 percent per annum is noted. Cognitive psychologists have established that as the brain ages, certain types of cognitive capacities do indeed decline. When designing mobile devices, the elderly should not be neglected since the future points to the use of technology to help the elderly people maintain their independence even if they develop age-related barriers, particularly in the use of technology (Kurniawan, 2007).

Table 2.1: *Indicators of population age 45 and above since 1969*

Indicator	**Census Year**				
	1969	1979	1989	1999	2009
Population size (millions)	0.8	0.9	1.4	1.7	2.6
Percent of total population	7.4	5.3	6.5	6.2	6.8
Growth rate (% p.a.)	-	0.6	4.8	2.5	4.2

2.2 Cognitive Load Theory and User Interface Design

As the design of the instructional material causes demands on the user, working memory capacity is reduced, making learning the material more difficult. The same applies to the design of software. The software causes undue demand on the users as a result of: being poorly designed such that it is unclear how to use the application, the data to be remembered is spread across multiple screens, or the way the software works conflicts with existing knowledge about the domain (Errey, Ginns, & Pitts, 2006).

2.2.1 Aging Cognitive Decline

Cognitive psychologists have established that as the brain ages, certain types of cognitive capacities do indeed decline (Backman, 2001). They include working memory, cognitive flexibility, ability to focus and processing speed.

Working memory: working memory is the capacity of the mind at any given moment to manipulate different types of information and perform complex tasks. The age- related decline in working memory affects the use and integration of new information with previous information (Sharit & Czaja, 1994). Excluding irrelevant information or materials from the interface design is one way to reduce the burden on working memory.

Cognitive flexibility: the ability to change decisions when given additional information that might otherwise alter one's opinion. Older adults are less able to engage in "divergent thinking," which is the ability to generate alternative explanations or solutions to a problem.
Ability to focus: Increased age often means increased difficulty in focusing on specific information and eliminating distractions. Some researchers theorize that it is this inability to rule out irrelevant details that clutters the working memory and lessens one's capacity to process information.

Processing speed: is related and varies with age where by advancement in age contributes to slower responses and longer reaction times. This could as well be explained by other age-related cognitive differences including attention and working memory. In computer-related tasks, processing speed affects older adults in finding information, keeping track of where information is, and sorting out relevant information (Backman, 2001).

When conducting tasks, different levels of attention are required for allocation and directing of cognitive resources. Age-related differences in performing cognitive tasks increase during dual task conditions (McDowd, 2000). The increased memory demands in attention leads to older adults performing slowly when switching between different tasks.

2.3 Mobile Device Navigation

Though mobile technology is one of the fastest growing technologies, usability challenges are still noted. Users mostly find difficulties and are weighed down using the technical devices and need to keep up with the sophisticated technology (Ziefle & Bay, 2006). The restricted screen space leads to a lot of information being hidden from the sight and only little information to be displayed on the screen at a time. Navigation places high demand on working memory in order to remember the correct buttons to press to reach the wanted functionality. This increases memory load since users have to memorize the location and path of the functions within the services (Sjölinder, 2003). Users do not understand the structure of the applications and how applications are arranged. This makes it difficult for users to build a mental representation of the space they are navigating because users often do not know where they are, where they came from, or where they have to go next (Ziefle & Bay, 2006).

2.4 Elderly User and Navigation

Users' age has been shown in many studies to affect navigation performance (Kelley & Charness, 1995; Lin, 2001; Pak, 2001; Ziefle et al., 2006). The elderly performance has been found to be consistently lower compared to that of younger adults, when maneuvering through the technology devices. The elderly experience greater difficulties during navigation; spend more time on accomplishing complex task, and they wander-off within the menu than did younger users. Their lower performance can be associated to the general age-related decrease of sensory, motor, and cognitive functioning (Fisk, 2004).

High influence on performance outcomes has been propagated by users’ spatial ability. In previous studies, users with high spatial abilities demonstrated considerably higher effectiveness and efficiency when using different technical devices compared to users with low spatial abilities (Arning, 2006; Egan, 1988; Maguire, 2004; Norman, 2004; Tuomainen & Haapanen, 2003; Vicente, 1988; Ziefle, 2005). Memory and spatial abilities have been found to decrease over the life span (Freudenthal, 2005). This may be credited to be the cause of reduced performance in older users.

The implication is that the elderly users declining capabilities, since well noted, calls for assistive methods to ensure that they are not left out in embracing the new technology because of the uncontrollable declining capabilities related to aging. A simplified user interface with predictive applications access to help compensate the users declining capabilities by presenting information in mobile devices serves to minimize memory demands, spatial abilities and cognitive flexibilities faced by the elderly users.

2.5 Navigation Techniques in Small Screen Devices

Approaches applied in previous research on navigating information spaces on small-screen devices include restructuring the information space; scrolling, panning and zooming; overview and detail approaches; overview and context approaches; and off-screen object visualization.

2.5.1 Restructuring the Information Space

To view large information spaces on small screens, researchers have often looked at restructuring the information space itself, especially in the case of web pages (Chen, Ma, & Zhang, 2003; Trevor, Hilbert, Schilit, & Koh, 2001). For example, a basic approach consists of manually designing web pages specifically for each target device (Jacobs, Li, Schrier, Bargeron, & Salesin, 2003). When this is not feasible, a possible solution is based on automatically reformatting pages (Bjork et al., 1999; Buyukkokten, Garcia-Molina, Paepcke, & Winograd, 2000). Most commercially available web browsers for mobile devices are able to reformat web pages by concatenating all columns, thus providing a single-column viewing mode.

However, these reformatting techniques significantly affect the layout of pages, thus making it difficult for users to leverage their experience with desktop web browsing. To solve this problem, researchers proposed to display web pages as thumbnails, i.e., scaled down versions of pages that fit the width of the small screen and are sometimes restructured to improve user recognition of their different parts. In this way, users can start viewing a web page in thumbnail mode to identify an area of interest, and then zoom into that area for reading. For example, Summary Thumbnails (Lamand & Baudisch, 2005) are thumbnail views that preserve the original page layout that allows users to recognize the overall page structure, but also contain readable summaries of the textual areas, so that users can disambiguate the desired information from similar looking areas.

The MiniMap method (Roto, Popescu, Koivisto, & Vartiainen, 2006) changes the size of the text relative to the rest of the page contents and limits the maximum width of the text paragraphs to the width of the browser viewport. An overview of the web page with an indication of the current viewport is then overlaid transparently on top of the browser viewport, thus providing users with a navigation aid and helping them to locate information inside the page.

2.5.2 Scrolling, Panning and Zooming

On mobile devices, various interaction techniques have been proposed to simplify scrolling, panning and zooming. For example, ZoneZoom (Robbins, 2005) is an input technique that lets users easily explore large images on Smartphones: each image is partitioned into nine cells, each one mapped into a number of the phone keypad, and pressing a key produces an automated pan and zoom on the associated cell (which can then be recursively partitioned into nine more cells). Rosenbaum (2005) propose an adaptation of the ZoneZoom technique to PDAs to pan and zoom on images by interacting with a grid overlaid on the currently displayed image portion.

The grid size is proportional to the size of the whole image and each grid cell can be tapped to zoom on the corresponding portion of the image. Cells can also be merged or split to provide users with different zoom levels. Jones (2005) takes the Speed-Dependent Automatic Zooming (SDAZ) technique proposed by Igarashi (2000) for navigating documents and adapt it to mobile devices. SDAZ combines scrolling and zooming into a single operation, where the zoom level decreases as scroll speed increases, and has been shown to outperform Standard scroll, pan and zoom methods in document and map navigation tasks (Cockburn, 2003).

In the SDAZ version by Jones (2005), two concentric circles are drawn when users tap on the information space with the pointer. If the pointer remains within the inner circle, the user is free to pan in any direction and the panning rate increases as the pointer moves away from the starting position. When the pointer moves beyond the inner circle, both zooming and panning operations take place. The information space progressively zooms out as the user moves closer to the outer circle and the panning speed changes to maintain a consistent visual flow. When the pointer reaches the outer circle, no further zooming occurs, while panning remains active.

Although scrolling, panning and zooming techniques allow users to explore an information space at different levels of detail, it is often useful to display more than one level of detail simultaneously.

2.5.3 Overview and Detail Approach.

These approaches provide one or multiple overviews of the space (usually at a reduced scale), together with a detail view of a specific portion of space (Plaisant, 1995) example, the Large Focus-Display (Karstens, 2004) provides two separate views of the information space, one for context and one for detail. The context view displays a downscaled version of the information space and highlights the portion of space displayed in the detail view with a rectangular view finder. Users can drag the view finder to navigate the information space.

By examining the size and position of the view finder in the context view, users are also able to derive useful information for navigation, such as the scale ratio between the displayed portion and the whole information space. Although Overview & Detail approaches have been found to be useful in desktop interfaces (Hornbaek, 2001), they are problematic on mobile devices, because the screen space that can be assigned to visualize overviews is typically insufficient to allow the user to easily relate them to the detail view (Chittaro, 2006). For example, Buring (2006) reports the results of a user study in which participants performed search tasks on scatter plots by using two applications on a PDA, one displaying a detail view and an overview and the other displaying only the detail view.

While there was no significant difference in user preference between the interfaces, participants solved search tasks faster without the overview. This indicates that, on small screens, a larger detail view can outweigh the benefits gained from an overview window. An alternative solution, such as displaying the overview on-demand, can save screen space but makes it impossible for the user to see the two views at the same time, requiring users to switch attention from one view to the other and to remember the contents of the un-shown view.

2.5.4 Focus and Context Approach

Focus and context techniques include: fish-eye views which integrates context and focus into single view (Sarkar, 1992), bifocal displays (Robertson & Mackinlay, 1993), and table lenses (Rao & Stuart, 1994). Fish-eye systems have been studied in a number of contexts, and have been shown to perform well for navigating networks (Schaffer et al., 1996), for using menus (Bederson, 2000), and for large tracing and steering tasks (Gutwin, 2003). However, distortion oriented techniques can also cause problems for some interactions such as targeting (Gutwin, 2002).

Techniques based on this Focus and Context approach usually display one or multiple focus areas with undistorted content embedded in surrounding context areas that are distorted to fit into the available screen space. In the Rectangular FishEye View (Rauschenbach, 2001), a rectangular focus is surrounded by one or more context belts, appropriately scaled to save screen space. Different schemes are used to choose the scaling factor for each context belt, in such a way that less detail is displayed as the distance from the focus increases.

A fish-eye view technique coupled with compact overviews is used in the DateLens calendar interface for PDAs (Bederson, Clamage, Czerwinski, & Robertson, 2004). The basic operation of DateLens is to start with an overview of a large time period using a graphical representation of each day's activities.

The Focus and Context techniques different scales and the introduced distortions make it more difficult for users to integrate all information into a single mental model and interfere with tasks that require precise geometric assessments (Patrick Baudisch, Good, Bellotti, & Schraedley, 2002). A Focus and Context technique allows users to explore areas of an information space at multiple levels of details by stretching or squeezing rectilinear focus areas (Sarkar, 1993). However, a study that compared a semantic zooming technique and a fish-eye view technique to support users in interacting with scatter plots on small screens found no significant difference in task-completion times and a higher level of user preference for the latter technique (Buring, 2006).

2.5.5 Off-screen Object Visualization

While Overview & Detail, and Focus & Context techniques can facilitate the exploration of large information spaces, they introduce additional interaction and cognitive costs that make them unsuitable for users who need large undistorted content to perform spatial tasks, such as first responders who need to identify locations of potential hazards in a building or view the real-time location of other team members on a map. To better support these users, one can enable them to locate relevant objects on the information space even when they are outside the area displayed in the viewport.

This is the approach followed by Mackinlay, et.al (2003), who proposed CityLights, i.e., compact graphical representations such as points, lines or arcs which are placed along the borders of a window to provide awareness about off-screen objects located in their direction. In a desktop scenario, City Lights lines have been used to inform users about the presence and size of hidden windows in a spatial hypertext system.

In mobile scenarios, a variation of CityLights, called Halo (Baudisch & Rosenholtz, 2003), shows off-screen object locations by surrounding them with circles that are just large enough to reach into the border region of the viewport. By looking at the position and curvature of the portion of circle visualized on-screen, users can derive the off-screen location of the object located in the circle center. A user study has shown that Halo enables users to complete map-based route planning tasks faster than a technique based on displaying arrows coupled with labels for distance indication, while a comparison of error rates between the two techniques did not find significant differences.

2.6 Adaptive User Interfaces

An adaptive user interface (AUI) can be broadly defined as an interface that can be modified based on the characteristics of its user. Grace (2004) gives a more precise definition of AUI separating the notion of user model from AUI. A user model is the component that implements the algorithms to capture and express personalization information. AUI takes the human perspective, and is the Graphical User Interface where the personalization information can be accessed and used. Adaptation can take place in three ways (Edmonds, 1987); the first way being at the request of the user, the second being by prompting the user to change the interface, and lastly by automatically adapting the interface. The difference between these methods is that the user is required to intervene in the adaption process. This difference is also reflected in the meaning of adaptive and adaptable user interfaces.

AUI usually refer to interfaces that automatically adapt to a user. Adaptable user interfaces rely on the user choosing the interface's characteristics. Adaptable user interfaces are defined by Kantorowitz (1989) as being able to support more than one dialogue mode, allowing a user to switch smoothly between dialogue modes at any time, and allowing a user to easily learn the different dialogue modes. Adaptable user interface relies on the user choosing the interfaces characteristics.

AUI systems are classified into informative and generative adaptive user interfaces. Informative interfaces can adapt by filtering information for a user and generative interfaces generate new knowledge structures that can be applied to assist the user.

2.7 Prediction in Android

As of March 2012, the number of apps and games in Android market reached about 620,000 and the total number of downloads was estimated to be over nine billion. Increasingly, large number of the apps installed on smartphones tends to decrease the application lookup efficiency and more time is required to manage them. A typical Android phone launcher by default places all app icons in the app drawer and the apps are usually ordered according to their installation time or alphabetically. Furthermore, the users could create shortcut for their favorite apps on the home screens directly or manage the shortcuts in folders. With a large number of apps installed, the users usually launch an app either by looking up the shortcut screen by screen (Android phone usually has more than one home screens) or by going through the prohibitively long app list in the app drawery (T. Yan, 2012).

Android is a collection of open source software used in mobile devices. The Android SDK provides the tools and API necessary to begin developing apps on the Android platform using the Java programming language. Android provides users with the opportunity to build and publish their own applications by providing an open development environment. The platform treats all applications (native and third-party) as equals.

2.7.1 Timestamping Measurements

Android exposes at least four different time sources to the programmer that include uptime, real-time, wall-clock time and external time sources. Uptime is the time span since the device was last turned on; it does not count time while the device is off. The real-time clock continues counting time while the device is off and tracks UTC. Wall-clock time is a real-time clock with attached time zone information; it is used for displaying the local time to the user. External time sources can be used to set the real-time clock to a known good value: network time can be obtained by querying a server for a reference timestamp and GPS time is a highly accurate source of timing information available on many Android devices. The most immediately appealing of these clocks is wall-clock time, as it represents time the way the user experiences it and allows us to capture diurnal patterns. However, both real-time clock and wall-clock time are subject to automated changes from the cellular network or a network time source and are affected by manual changes by the user. An application using these clocks would record time in a non-linear fashion, which may include overlaps if the time was set back. In particular, we have frequently observed devices reporting a date in the 1980s for a short period of time when they first start up after an operating system upgrade.

2.7.2 Naïve Bayes Classifier

Naïve Bayes classifiers represent a supervised learning method as well as a statistical method for classification. The classifiers assume an underlying probabilistic model that allows users to capture uncertainty about the model in a principled way by determining probabilities of the outcomes. This classifier learns from training data the conditional probability of each attribute A_i given the class label C. Classification is then done by applying Bayes rule to compute the probability of C given the particular instance of $A_1,...,A_n$, and then predicting the class with the highest posterior probability. This computation is rendered feasible by making a strong independence assumption: all the attributes A_i are conditionally independent given the value of the class C. By independence it means probabilistic independence, that is, A is independent of B given C whenever $Pr(A|B,C) = Pr(A|C)$for all possible values of A, B and C, whenever $Pr(C) > 0$(Friedman, Geiger, & Goldszmidt, 1997).

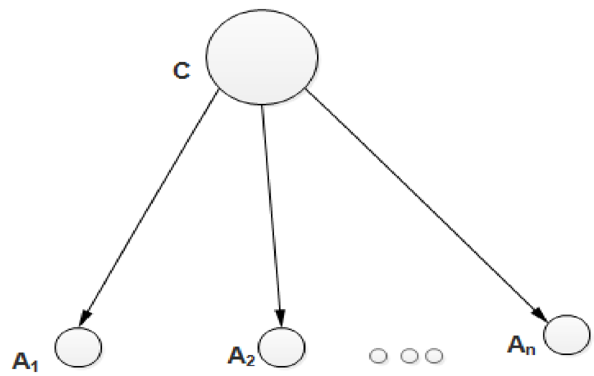

Figure 2.1: *The structure of the naive Bayes network*

Depending on the precise nature of the probability model, Naïve Bayes classifiers can be trained very efficiently in a supervised learning setting. In many practical applications, parameter estimation for Naïve Bayes models uses the method of maximum likelihood; Naïve Bayes models are also known under a variety of names in the literature, including Simple Bayes and Independence Bayes (Hand & Yu, 2001).

An advantage of Naïve Bayes is that it only requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix.

In spite of their naive design and apparently over-simplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations. In 2004, analysis of the Bayesian classification problem has shown that there are some theoretical reasons for the apparently unreasonable efficacy of naive Bayes classifiers (Caruana, Munson, & Niculescu-Mizil, 2006).

2.8 Assistive Technology

Assistive technology (AT) is technology used by individuals with disabilities in order to perform functions that might otherwise be difficult or impossible. Assistive technology can include mobility devices such as walkers and wheelchairs, as well as hardware, software, and peripherals that assist people with disabilities in accessing computers or other information technologies. Definition proposed in the Assistive Technology Act of 1998.

2.8.1 Goals for Assistive Technology in Cognition

Assistive technology can assist older people with cognitive impairment (Callahan, Hendrie, & Tierney, 1995) in following ways:

i. By providing assurance that the elder is safe and is performing necessary daily activities, and, if not, alerting a caregiver; e.g. assurance systems aim primarily at ensuring safety and well-being and at reducing caregiver burden, by tracking an elder's behavior and providing up-to-date status reports to a caregiver
ii. By helping the elder compensate for her impairment, assisting in the performance of daily activities; e.g. compensation systems provide guidance to people as they carry out their daily activities, reminding them of what they need to do and how to do it.
iii. By assessing the elder's cognitive status; e.g. assessment systems attempt to infer how well a person is doing what his/her current cognitive level of functioning is based on continual observation of his/her performance of routine activities.

In all three cases, it is essential that the system be able to observe and reason about the elder's performance of daily activities (Boise, Neal, & Kaye, 2004). This is probably most obvious in the case of assurance systems, which must recognize whether someone has fallen, has eaten, has taken her medicine, and so on. In addition, the ability to recognize the performance of routine activities is also essential for compensation systems, so that they can provide useful assistance that is tailored to the current needs of the user. Similarly, assessment systems work by reasoning about how and when the user performs his/her daily activities.

2.8.2 Assurance Systems

These systems include sensors placed in the user's home, communicating via a short-range protocol such as X10 to a base station, which may in turn communicate wirelessly to a controller; the controller then uses broadband or a "plain old telephone system" (POTS) to send information to a monitoring station or directly to the caregiver. Caregivers can get status reports on a regular basis, typically by checking a web page, and are also alerted to emergencies by phone, pager, or email. Assurance systems examples include research projects (Haigh, 2002; Kart, Kinney, Murdoch, & Ziemba, 2002; Chan, 1999; Ogawa & Suzuki, 2002), a demonstration system being used in an elder care residential setting (Stanford, 2002), and a handful of commercially marketed products.

In some cases, the sensor network used by an assurance system is extremely simple, consisting, of just contact switches on external doorways, so that a care giver can be immediately notified if a cognitively impaired elder leaves his/her home: wandering is a significant problem for people with certain types of cognitive impairment. With these systems, very little inference is actually required; instead, an alarm is simply generated whenever the contact is triggered.

In other cases, the network may include a wide range of sensors, which are continually monitored both to recognize deviations from normal trends that may indicate problems (for example, failure to eat meals regularly, as determined by lack of motion in the kitchen) and to detect emergencies that require immediate attention (for example, falls, as indicated by cessation of motion above a certain height). The sophistication of the inference performed using the collected sensor data varies from system to system. In some systems, only a loose connection is established between the sensor signal and the activity being reported on; machine learning may be used to infer broad patterns of sensor firings, which then serve as the basis of establishing deviations from the norm that constitute grounds for issuing a warning.

2.8.3 Compensation Systems

These systems can help compensate for impairment in the ability to navigate, to manage a daily schedule, to complete a multistep task, to recognize faces, and to locate objects. Several systems have been developed to help older adults navigate successfully around their environments. Most of these systems aim to assist people who can no longer safely find their way around, because of either sensory difficulty such as diminished vision or mobility impairments that make walking difficult. A major goal of these systems is obstacle avoidance. One interesting example of a system that provides navigational support to people with cognitive impairment is the intelligent mobility platform (IMP) (Morris & Donamukkala, 2003), IMP consists of a standard commercial walker augmented with a laser range-finder, a handheld computer providing a touch screen interface for the user, an active drive mechanism, and intelligent navigation software. The goal of the IMP project has been to design a device that can help a potentially confused user find his/her way around a setting, such as a large assisted-living facility, in which she might otherwise become lost.

Another type of compensation system is schedule management system which helps users who have suffered from memory decline that makes them prone to forgetfulness about routine daily activities. In particular, they remind people when to take their medicine, when to eat meals, when to take care of personal hygiene, and when to check in with their adult children. Early schedule-management systems used alarm clocks, calendars, and buzzers (Harris, 1978; Jones, 1999; Wilson, 1994), while later systems employed wireless devices including pagers, cell phones, and palmtop computers (Hersh, 1994; Kim & Boone, 2000; Wilson, 1997).

2.8.4 Assessment Systems

Several researchers have thus begun to explore the possibility of using sensor-based monitoring, combined with sophisticated analysis algorithms, to assess a person's level of functioning as she goes about her routine activities in his/her home. An example is Wired Independence Square, a project in which sensors are placed in a kitchen and used to collect timing data while a patient at risk for cognitive impairment performs a task such as making tea (Carter, 1999). The hypothesis, as yet un-confirmed, is that objective data such as this has been shown to correlate with assessments made with standard diagnostic batteries such as the Assessment of Motor and Process Skills (AMPS), a tool used by occupational therapists to measure the quality of a person's performance of activities of daily living.

In initial studies, each user was monitored as she played an adapted version of the FreeCell solitaire game; this was selected both because interviews with older adults showed that they enjoyed this activity and because it is one that incorporates aspects of cognition such as short-term memory and strategic planning that are directly relevant to the performance of activities of daily living. Each time the user played FreeCell, her performance was compared to a standard established by an automated solver. Analysis was then done to track the user's relative performance over time; the goal was to identify declines in performance that could be indicative of more general cognitive decline.

2.9 Assistive Technology in ICT

Assistive technology involves the use of an assistive invention to fill the gap between the needs of the user interface of the device and the abilities of the user (Mellors, 2001).

It is required by a user of ICT technology whenever the person's disability is such that they cannot operate the technology safely and efficiently. From a technical point of view, a person with any disability requires assistive technology to use ICT equipment whenever they;

1. Cannot operate the controls (for instance because of their physical disability);
2. Cannot obtain information from the device (for instance because of their sensory disability);
3. Cannot understand how to operate the device (for instance if they have a cognitive disability).

The complexity of matching a person and technology arises not only from the individual's unique combination of physical, sensory, and cognitive abilities but also from people's expectations and reactions to technologies (Scherer, 2005). These reactions emerge from personal needs, abilities, preferences, and past experiences with and exposures to technologies. Pre-dispositions to technology use also depend on factors such as one's temperament personality, subjective quality of life/well-being, views of physical capabilities, expectations for future functioning, financial and social-environmental support, and facilitators for technology use (Scherer, 2005).

In this study the proposed assistive technology was a compensation system that could assist the elderly users in navigating mobile device user interface applications using an application predictor. The predictor can forecast the applications that are likely to be accessed by the user, thus providing an adaptive user interface which does not demand the user to remember the process of accessing the predicted applications resulting to ease of navigation.

2.10 Human Activity Assistive Technology Model (HAAT)

This is a general model for an AT system. It shows the interrelationship between system components. Human Performance Model (Cook & Hussey, 1995) was developed by human factors engineers and psychologists to assist in the design and application of technology. It is a framework for studying human performance in tasks involving technology.

The model is used to typically describe the performance of a human in a given task (activity) in a given situation (context - environment). Figure 2.2 relates the human performance model with the modified human assistive technology model. In HAAT model for an AT system the context environment constitutes of three components human, activity and assistive technology which for this research is the intelligent mobile applications predictor.

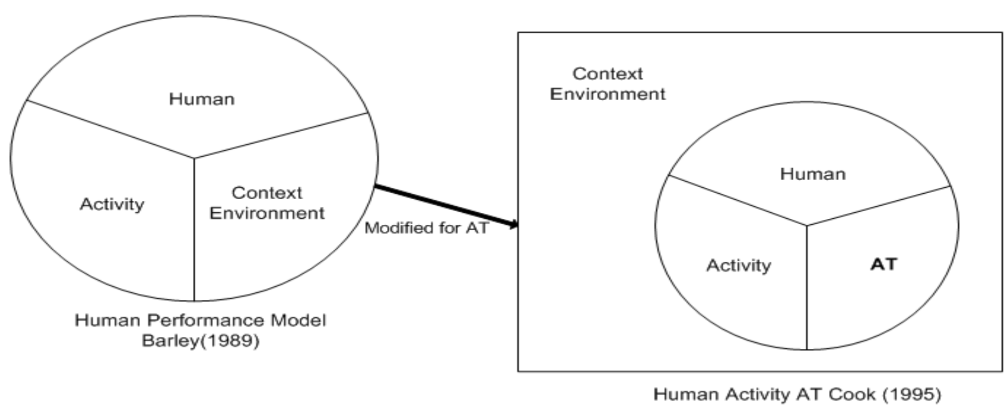

Figure 2.2: *Assistive Technology Model*

The activities an individual performs are determined by that person's life role(s), examples of performance areas include self care, work/school, play/leisure. The need to know what tasks a person performs helps determine points at which an individual may need assistance to accomplish activity. In this study the activity refers to the user access to the mobile devices numerous applications and navigation through them.

Human (intrinsic enabler) refers to the operator and their underlying abilities (sensory input, central processing and motor output). There is need to take into consideration the person's skills and abilities. In this study human refers to the elderly user operating a mobile device and have declining cognitive ability. Context refers to where the activity is being performed, the setting (environment).

In this study the context refers to the mobile device user interface. The AT (extrinsic enabler) provides basis that allows human performance it consists of both hard technologies i.e. human/technology interfaces, activity output, processor, and soft technologies i.e. performance aids, written instructions, and training. In this study AT is represented by the proposed predictive algorithm that captures/monitors applications accessed, track frequency of access to each application, assign time stamps to applications, assign the values for health and cost benefit of the application whether True or False in order to predict the applications that are most likely to be accessed by the user and present them in a simplified adaptive user interface.

Relating to the general model for AT system (HAAT) by Cook and Hussey (1995). This study's AT presents an intelligent application predictor for mobile devices which can:

i. Predict the applications which are most likely to be accessed by the user on his/her mobile device.
ii. Present a user centric interface that is simplified and adaptable in line with the user requirements.

2.11 Summary

A considerable amount of research has been conducted into adaptive user interfaces. This research prediction approach attempts to compute user tasks using the most common menu-item approach adaptive algorithm (Bridle & McCreath, 2005); a concept that can be used to predict a user's action, hence it can be considered a generative adaptive interface (Benyon, 1993). Many generative interface applications exist, these include; programming by demonstration (Alexander, 1998), scheduling and user modeling applications (Blackwell, 2002). The generative interface task that closely matches this research is action prediction using command line prediction (Amant, 2004;

Bartlett, Ben-David, & Kulkarni, 2000); most closely is an action prediction investigated within graphical user interfaces (GUI).

Bao et.al (2006), present Folder Predictor, a system that predicts which folder in a GUI folder hierarchy a user will access. Folder Predictor generates its predictions by applying a simple machine learning method to a stream of observed file open/save events. Each of these events includes the name of the folder, containing the file that was opened or saved. For each task, Folder Predictor maintains statistics for each folder, how many times the user opened files from it or saved files to it. This research shares challenges faced in applying prediction to menu interface. Both must predict the next action the user is going to perform by inferring the current task a user is performing, and both must increase interface efficiency while maintaining interface predictability.

However, applications adaptation may be a more assailable task, as the number of possible tasks that can be presented in a menu is usually quite small. Therefore, this approach improves on majority of action prediction systems by, besides predicting and adapting the frequently accessed applications, considering other properties of the application i.e. the time elapsed, health benefit and economic benefit of the application to the user in order to predict the more important application that the user is likely to access. This assists the elderly to access their predicted applications on mobile devices easily and faster.

Study by Francone (2009) presents Wavelet, the adaptation of the Wave menu for the navigation in multimedia data on iPhone. Its layout, based on an inverted representation of the hierarchy, is particularly well adapted to mobile devices. It guarantees that submenus are always displayed on the screen and it supports efficient navigation by providing pre visualization of the submenus. It allows user to see the content of a submenu when she drags the mouse over the corresponding menu.A study by Leung (2008) where navigation was implemented using the learnability principle for usability in a multilayered approach where users were to learn using a software application by starting with a reduced functionality layer that only allows user to perform basic task functions. Once they felt that they had mastered this layer, they transitioned to other layers and learnt to perform more advanced tasks. This approach aimed at reducing the complexity of the interface through focusing user's attention on learning key aspects of the interface.

Though, still memory load is needed to remember the tasks. Another study by Smyth (2002) adapts portal navigation structures for the needs of individual users using an intelligent system Clix Smart Navigator by Changing Worlds Ltd., as a solution that automatically adapts the navigation structure of a portal, reduces the effort required for a user to locate relevant content. Navigator tracks user accesses to individual menu options using hit tables; hash-tables keyed on menu *ids* and storing a list of accesses made by that user to options within that particular menu.

Lastly, another study by Park (2006) highlights use of submenu window as a navigation aid for mobile Internet access on a cellular phone. The submenu window presents child-level menu items along with their upper-level menu. It involves use of an aiding tool that can assist searching a target menu item; the tool presents the child-level menu items of a specific (defined as focused in this study) item in the current-level menu at the same time. With this tool, the users can peep in the submenu items without actually entering the submenu.

These studies show the previous efforts and employed approaches to overcome the menus navigation problem. They employed a Design for All approach which normally aims at ensuring that the product can be used by many users within their capabilities. As a result a group of people who are facing some challenges due to declining capabilities may be overlooked, therefore an assistive technology design approach for navigation should be considered to cater for the need of these special groups.

CHAPTER THREE
METHODOLOGY

3.1 Introduction

This research sampled a number of elderly people for their experiences and opinions about mobile devices navigation. The sample group constituted of the elderly in Kenya preferably working and retired civil servants. The sample group fit older people, who do not appear to be disabled, nor consider themselves disabled, and the age-related cognitive decline may be present.

For the purposes of the study, elderly people were considered as people aged 45 years and above, since they have adapted the new technology of smartphones and are aging. The group of people who participated in the study was between 45 and 65 years.

Literature review was the initial phase to get the current state of research on elderly in mobile devices interactions. Different keywords relevant with the research topic were used to search the materials available by well-known scholars.

3.2 Data Collection Method

Data collection was effected using a questionnaire. The questionnaires were structured using different types of questions such as open, list, category and rating/scale (Saunders, 2003). Open questions are used to collect information that cannot be put as a choice or in a scale, and where each participant may provide a different answer; the questionnaires prepared were presented to my supervisors and corrections were attended. Upon their approval, they were made available via the Internet (online) as well as distribution to the participants physically.

In order to determine the experiences and requirements by the elderly, a study (Appendix 1) was carried out in regard to mobile devices navigation, the study focused on the aging limitations, the length of use, the type of mobile device, the preferred icon layout, screen size and the preferred number of icons on the active screen, and also the preferred usability factors by the elderly.

3.3 Sample Size

A representative sample of the population was selected based on Cochran's formula for computing sample from a large population (Kasunic, 2005).

$$n_0 = \frac{Z^2 pq}{d^2} \tag{1}$$

Where;

$n_0 =$ The desired sample size given the target population is greater than 10,000.

$Z =$ The standard normal deviation (abscissa of the normal curve) at 95% confidence level (=1.96).

$p =$ The proportion in the target population estimated to have the characteristic being measured, if 50%, $p = 0.5$ i.e. at maximum variance.

$q = 1 - p$

d = The level of statistical significance (= 0.05). The significance level was taken at 95% with a margin error of 5%.

$$n_0 = \frac{(1.96)^2 (0.5)(0.5)}{0.05^2} = 384.16$$

$$n_0 \approx 384$$

The sample size can be adjusted when the population is less than 10,000 using the following relationship (Mugenda & Mugenda, 2003).

$$n_1 = \frac{n_0}{1 + (n_0 \div N)} = 60.95$$

$$n_1 \approx 61$$

Where:

$n_1 =$ the desired sample size when population is less than 10,000.

$n_0 =$ the desired sample size when population is more than 10,000 (=384).

N = the estimated population size (= 72 in this case).

$n_1 = 60.95 \approx 61$

The target sample size was therefore 61.

3.4 Sampling Procedure

Stratified sampling was used to divide Nairobi County into regions in order to get an inclusive sample. Random sampling technique was then used to select respondents from the target population of older adults in the stratified regions of Nairobi County. The questionnaire that was developed was circulated among the respondents and picked at a later date. An online version of the questionnaire was also developed and circulated among the randomly selected respondents to reduce on the response time.

3.5 Predictive Assistive Technology Approach

The proposed approach is as depicted on figure 3.1. It relates the HAAT (Cook, 1995), model and the proposed Assistive technology, the improvements on the standard user interface to realize the adaptive elderly centric interface. The generic user interface refers to the standard mobile device interface/window with the manufactures user interface design in place i.e. the menus/applications structure organization. This depends with the make and model series of the device since they differ from manufacturers.

Generic user interfaces are modified to a simplified user interface for the elderly after the prediction and adaptive process. User tasks are monitored and stored over time. The frequency of access, time elapsed, cost and health benefit of the application are computed; predicted applications that are most likely to be accessed are presented in a simplified user interface.

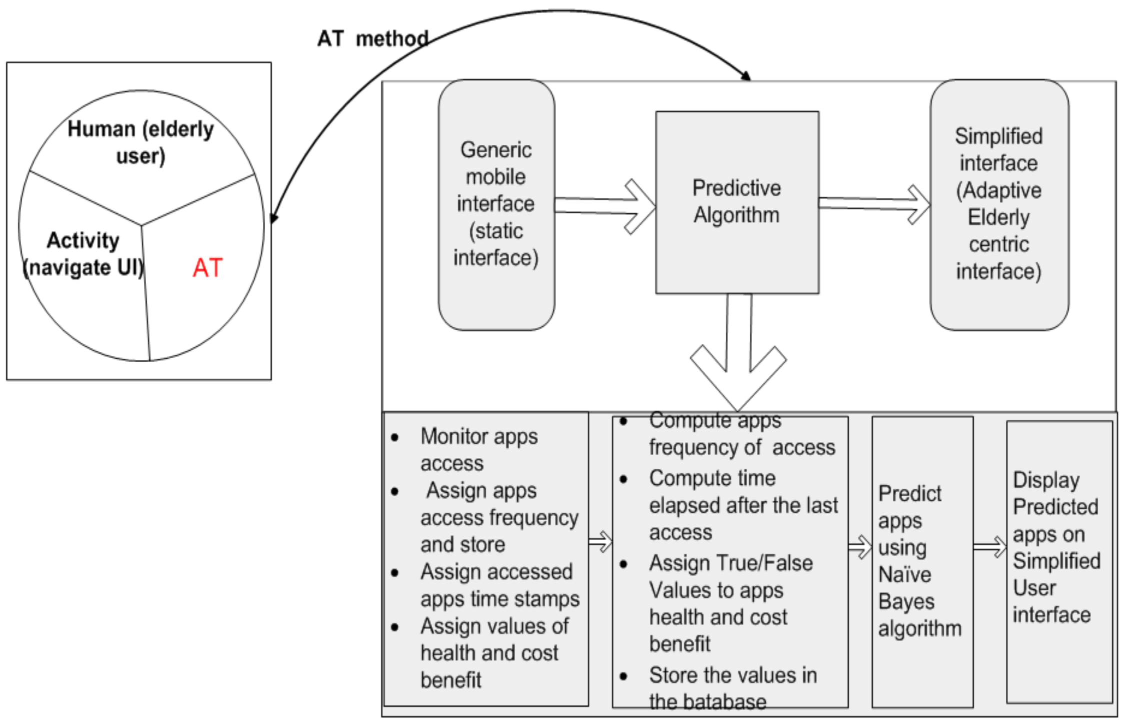

Figure 3.1: *Application prediction approach*

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CHAPTER FOUR
DATA ANALYSIS

4.1 Mobile Devices User Requirements

Results on mobile device platform are shown in figure 4.1. Where android phone has the highest percentage of use compared to the other platforms in the market. This agrees with the current market trends that depict the Android platform as being on the lead in terms of adoption and usage.

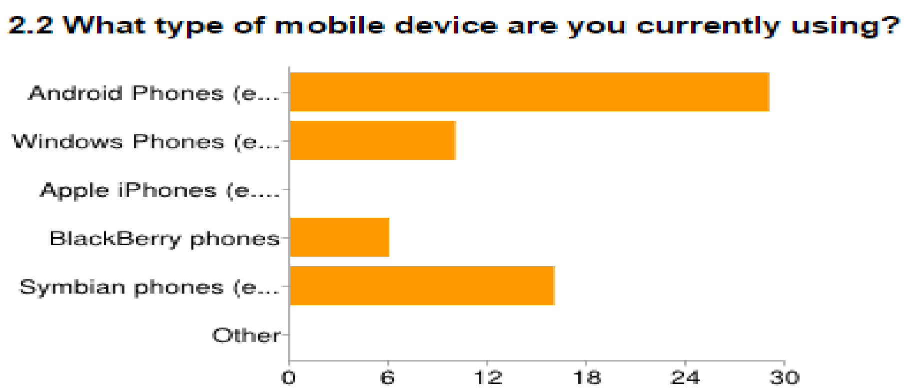
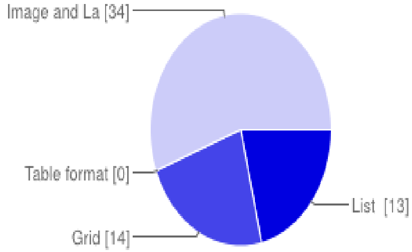


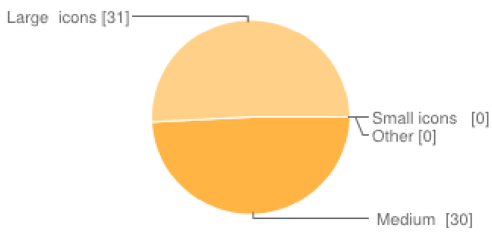
Figure 4.1: *Mobile Platform*

4.2 Users preferred icon layout and size

The preferred icon layout is depicted on figure 4.2. Both grid, image and icon layouts were preferred by 79% of the users; 49% of the users preferred medium sized icon layout while 51% of the users preferred large sized icon layout.



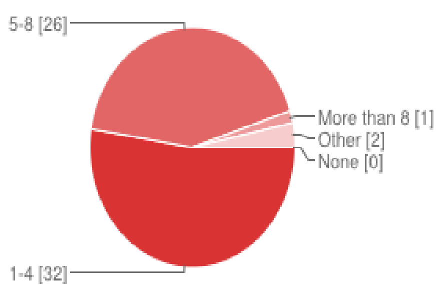
List	13	21%
Grid	14	23%
Table format	0	0%
Image and Label	34	56%



Small icons	0	0%
Medium	30	49%
Large icons	31	51%
Other	0	0%

Figure 4.2: *Icon layout and size*

Figure 4.3 shows the respondents preferred number of applications on their device home screen. 52% of respondents preferred 1-4 functions to appear on the mobile device main screen.



None	0	0%
1-4	32	52%
5-8	26	43%
More than 8	1	2%
Other	2	3%

Figure 4.3: ***Number of applications***

4.3 Navigational Challenges

The navigational challenges are as indicated in table 4.1. At 92.2%, the majority of the older adults experienced a combination of challenges while navigating mobile device interfaces that included small screen sizes, small font sizes and difficulties in using the touch screens. Some had challenges in locating essential features and applications in addition to the screen sizes being too small to output all the necessary and required information at once. The table below (4.1) shows the combination of different challenges that are faced by the elderly when navigating the mobile device interfaces in terms of percentages. The results shows that a combination of small screen sizes, small font sizes and difficult in using the touch screen (22.2 %) is the biggest challenge facing them.

Table 4.1 ***Challenges faced while navigating mobile device screens***

Challenges faced while navigating mobile device screens			
	%	Valid %	Cum. %
Small font size		14.8	14.8
Difficult in using the touch screen		11.1	25.9
Small font sizes and difficult in locating essential features and applications		11.1	37.0
Small screen sizes, small font sizes and difficult in using the touch screen		22.2	59.3
Small font sizes, difficulties in matching images and their functions, arrangement of applications on mobile device interface, difficulties in using the touch screen		3.7	63.0
Small font sizes, limited input features, difficulties in matching images and their functions, difficulties in locating essential features and applications, arrangement of applications on mobile device interface, difficulties in using the touch screen		3.7	66.7
Small screen sizes, limited input features, difficulties in locating essential features and applications		3.7	70.4
Limited input features, difficulties in matching images and their functions, difficulties in locating essential features and applications, difficulties in using the touch screen		3.7	74.1
Small font sizes, limited output features, difficulties in locating essential features and applications		3.7	77.8

Small font sizes, difficulties in using the touch screen	3.7	81.5
Limited output features, difficulties in using the touch screen	3.7	85.2
Small screen sizes, small font sizes	3.7	88.9
Small screen sizes, limited output features	3.7	92.6

4.4 Length of Device Usage

The length of using a mobile device determines the kind of navigational challenges experienced. The regression graph(s) in figure 4.4 shows that older adults experience more challenges while navigating mobile device interfaces as a result of aging.

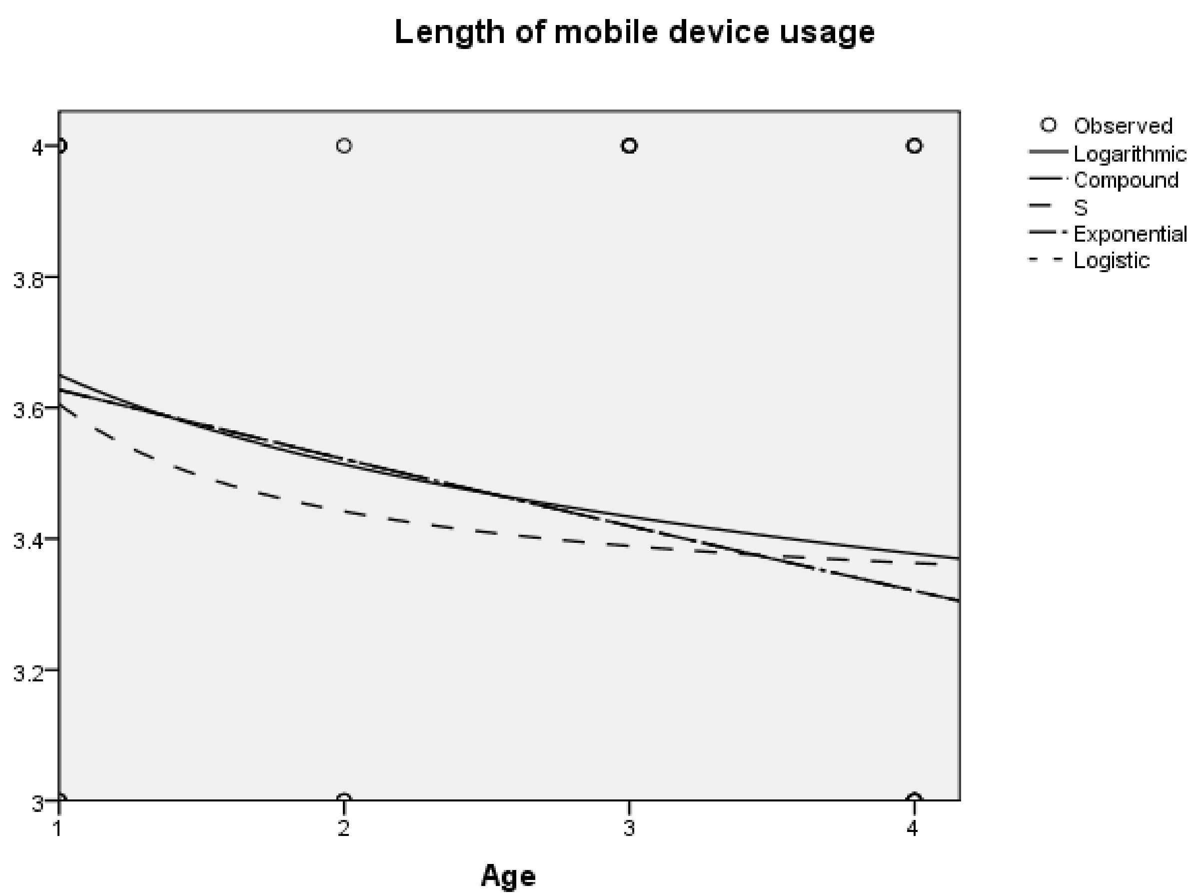


__Figure 4.4:__ Length of mobile device usage

4.5 Age Limitations

Fewer navigational challenges are experienced at the onset of older age and those challenges become more pronounced with the advancement of age as depicted on figure 4.5. The results of the kind of challenges faced show that 22.2% of older adults experience a combination of navigational challenges; this is depicted in figure 4.6. It represents the cross tabulation of the age limitations and the kind of challenge the user experiences while accessing the applications.

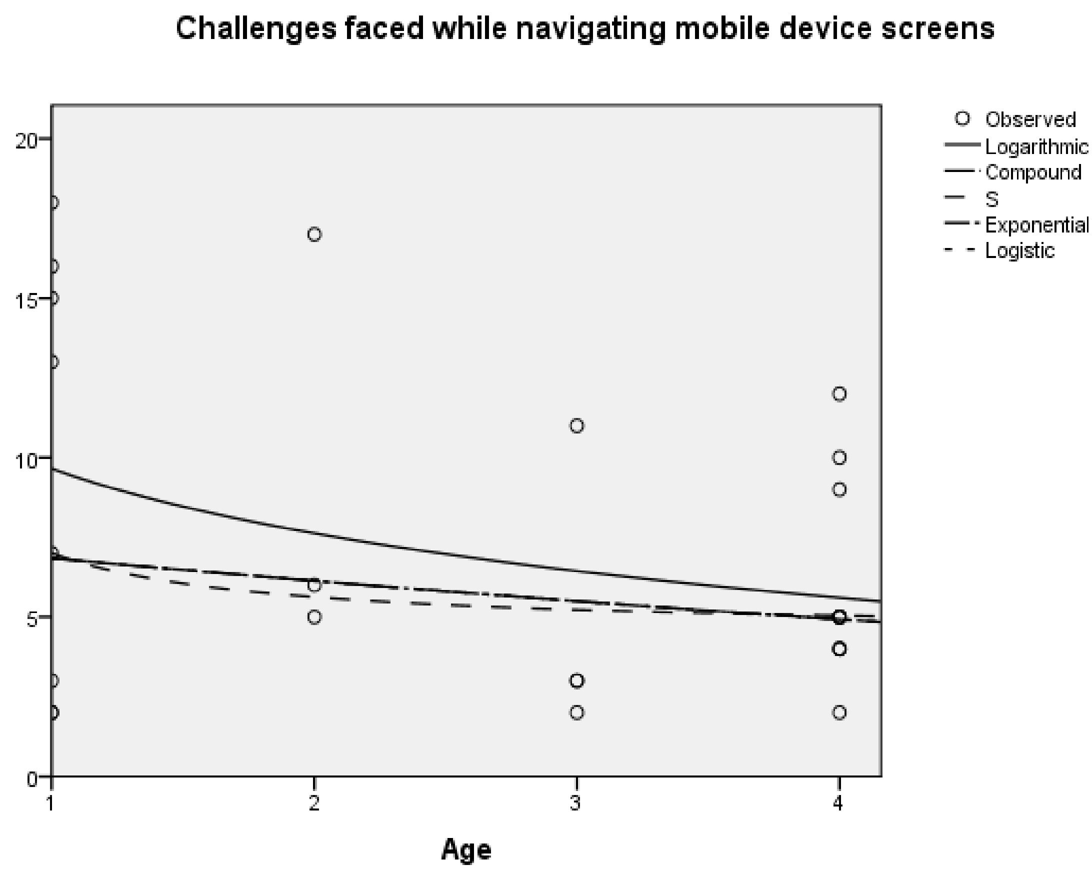


Figure 4.5: *Challenges faced while navigating mobile device screens*

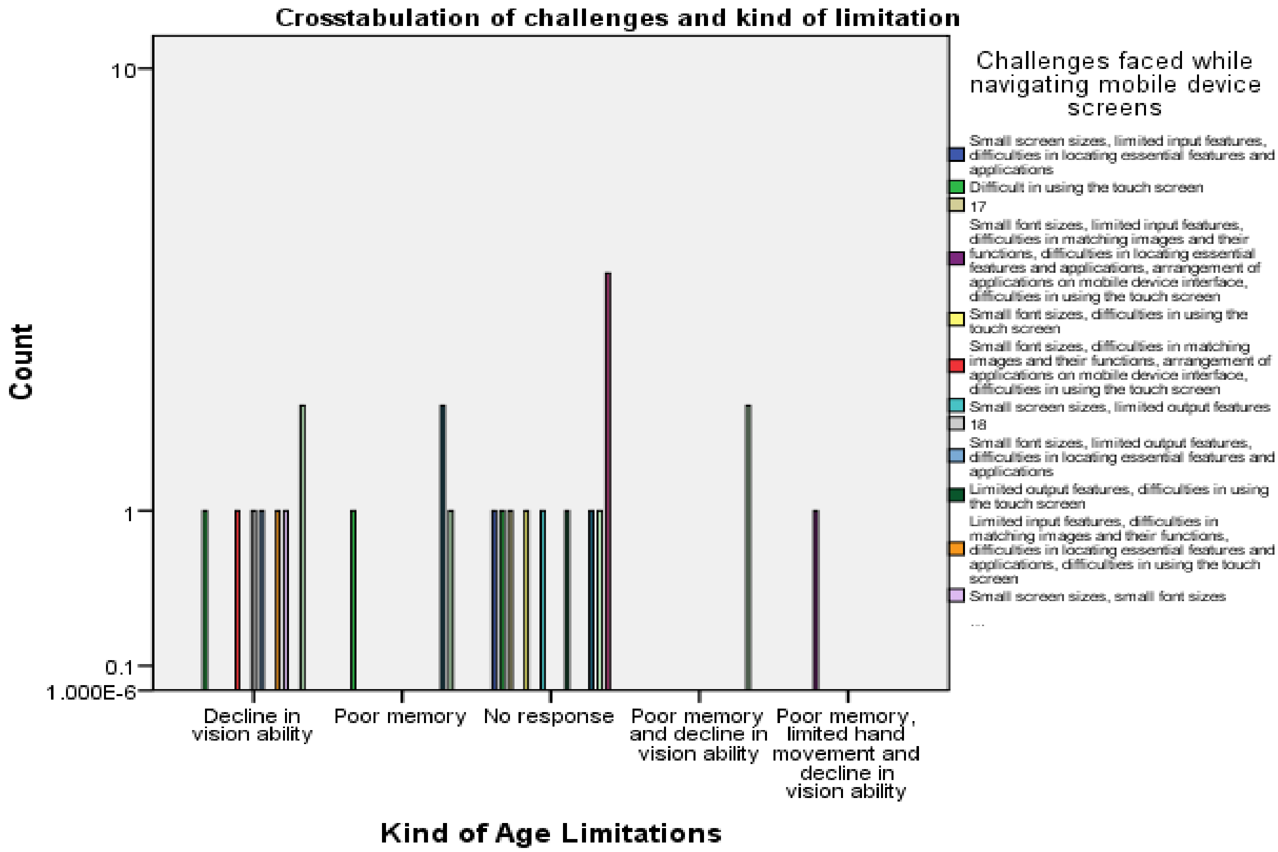


Figure 4.6: *Challenges and kind of limitations*

4.6 Preferred Features to Ease Navigation

Table 4.2 shows the user ratings on the features they would prefer to use to ease their mobile devices applications navigation and the summary of the rating responses. Highest rated feature was a mobile device interface that adjusts to user's preferences with 84% of the respondents rating it important to very important. Mobile interface that predicts user applications was as well rated important to very important by the respondents.

Table 4.2: *Preferred Features to Ease Navigation on Mobile Devices*

Preferred features	**Not important**	**Quite important**	**Important**	**Very important**	**Max No. of responses**
Large font size	0	9	33	19	**33**
Usage of images instead of plain text	3	13	22	23	**23**
Short cuts	5	15	29	12	**29**
Voice activation	7	17	25	12	**25**
Emergency call button	5	23	20	13	**23**
Audio display: a function to read aloud menus and pressed keys	16	14	21	10	**21**
Mobile device interface that predicts frequently used applications	3	18	31	9	**31**
Mobile device interface that predicts user's applications	6	11	28	16	**28**
Local language selection option	8	26	16	11	**26**
Mobile device interface that adjust to user's preferences	4	6	39	12	**39**
Preference	**16**	**26**	**39**	**23**	

4.7 Summary

In relation to user limitations, most participants have limitations in vision decline and poor memory therefore development of the assistive technology proposed should consider this limitations. For the case of the development platform, from the responses, android phones have the highest percentage of use (Fig.4.1) and therefore is the selected environment for developing the assistive model.

Preferred icons size and layout, from the responses, medium sized icons with grid, image and label layout displayed in 1-8 functions are most preferred as shown in (Fig. 4.2). The interface design for the application predictor will apply these specifications. Adaptive UI was rated as important to very important by the highest number of respondents. Mobile interface that provided navigational support for the aging was rated very important by highest number of respondents.

CHAPTER FIVE

APPLICATIONS PREDICTOR DESIGN

5.1 Introduction

This chapter discusses the applications predictor model design. It the details for the predictor architecture and prototype design and frequency architecture design. The chapter also gives the ways in which the time elapsed is computed.

5.2 Predictor Architecture and Prototype

The predictor system architecture is as shown on figure 5.1. The system encompasses a number of sub-systems that include the database, model trainer, feature extractor, decision engine, context source manager and the dispatcher. The model architecture offers architecture in which to systematically observe and utilize context and execute predictive application launch actions (Tingxin Yan, 2012). Home screen refers to the predictor main interface i.e. the mobile device UI where both predicted and frequently accessed apps are presented.

The logical flow of activities and interactions of different processes is taking place in the kernel. The central component is the launch predictor. Its role is to use context source attributes to predict app. The launch predictor’s feature extractors convert raw data from context sources into features for the decision engine and model trainer.

The database stores all the information for the prediction engine including the training data. The model trainer retrieves training data from the database and stores the resulting models back into the database. The trained models are used by the decision engine to determine the applications to be sent to the home screen by the dispatcher. The feature extractor gets information on the frequency of accessing applications; the time elapsed between periods of access, health and economic benefits and relays the information to the model trainer. The model trainer records observed features in order to periodically train and update the decision engine and feature extractors with new parameterizations. Note that, training occurs infrequently and is only critical when access patterns change significantly, whereas inference occurs frequently and is required whenever a launch prediction is made.

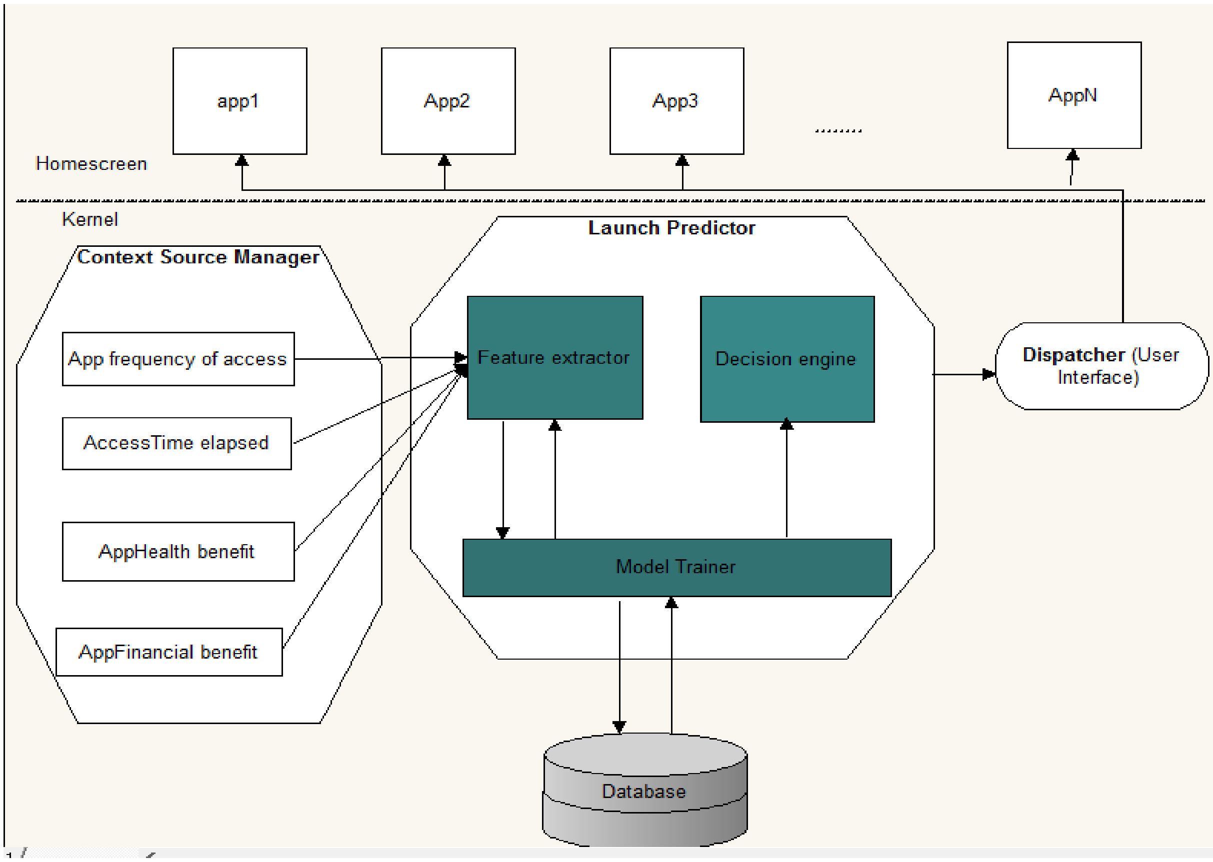


Figure 5.1: *Prediction system architecture*

The decision engine performs inference to determine which features to use and what applications to predict. The prediction is then passed on to the dispatcher, which loads apps into memory and executes the prelaunch routine of the selected app(s). The process tracker handles communication with the kernel's memory manager in order to ensure that the decision engine's view of the apps running on the system is in sync with what is actually running. Supporting the launch predictor, the context source manager is a lifecycle manager and container for various context sources. It also helps shepherd raw data from individual context sources to the launch predictor. Dispatcher refers to the output end of the decision engine i.e. the predicted apps.

5.3 Frequency Architecture

The most commonly accessed applications are determined through the frequency of access. The frequency architecture is as indicated by the flow chart on figure 5.2. To determine the frequency of application access, the architecture gets information on the last time the application was accessed and compares that with the information in the database regarding the application. If the application was already captured in the database previously, the frequency of access is incremented by 1. The model waits for a finite number of seconds and then polls the recent applications again. For this study the finite wait time, t was set to five (5) seconds.

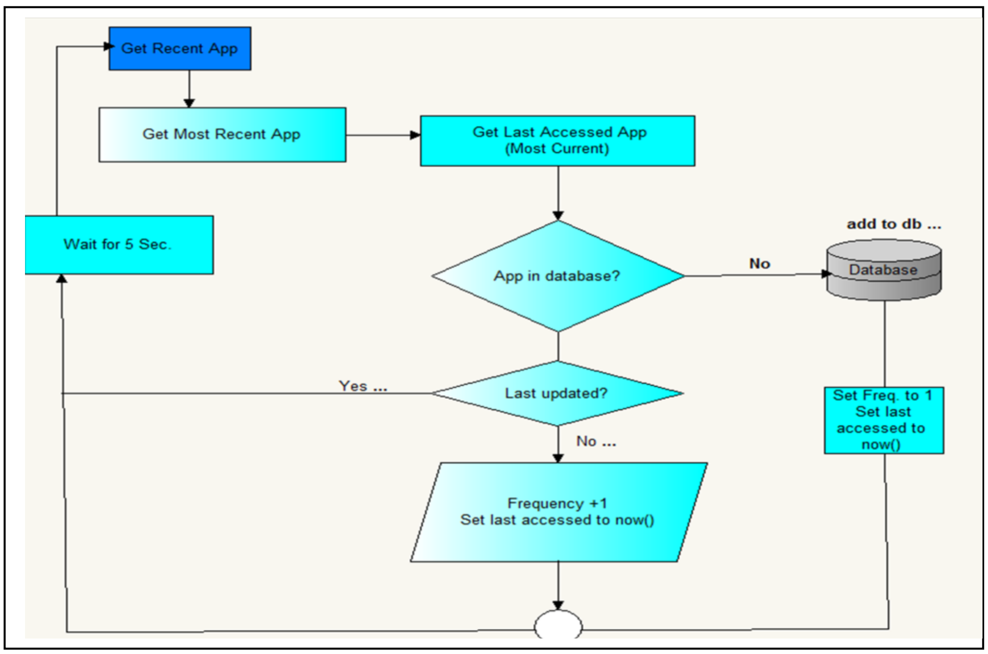


Figure 5.2: *Frequency architecture*

5.4 Time Lapsed

Time elapsed is used to capture the time when application was last accessed to help in determining the importance of that particular application to the user and then it can be rated accordingly. If the application is accessed at short intervals then it is rated high.

Time of access is defined by the time elapsed after accessing an application (2).

$$\tau = \omega_t - \psi_t \qquad (2)$$

Where τ is the time elapsed in hours;

ω_t is the current time in hours;

ψ_t is last time of application access in hours.

5.5 Health benefit

This is predetermined and assigned a random value of either true or false. The health benefit is context dependent and therefore may not be generalized. Different users have varied health requirements i.e. seek for different kinds of information on health using mobile applications. Therefore, at no particular time one can find a generalized health requirement that cuts across all the users.

5.6 Economic benefit

This is predetermined and assigned a random value of either true or false. The economic benefit depends on the situation and context of the user. Different users have varied uses for mobile applications. For example, some would use the applications for managing personal finances and others would the apps for managing fleets of vehicles.

5.7 Application Prediction Algorithm

In this study, the prediction process aim is to predict the mobile applications that the user is most likely to access on his/her device.

The application prediction and algorithm parameters are defined as follows;

Step 1: Monitors user accessed applications, A_m on the mobile device

Step 2: Stores user tasks, C_s

Step 3: Track Frequency of applications access, F_r

Step 4: Assign accessed applications timestampsT_e

Step 5: Selects applications with the highest usage frequency, generates an active window, A_w

Step 6: Assign the applications accessed health benefit random values of True/False H_b

Step 7: Assign the applications accessed financial benefit random values of True/False C_b

Step 8: Generate the training data set by assigning each attribute the values to guide in classification.

Computations for Predicted Application

With the goal of generating the simplified adaptive user interface with the applications that are most likely to be accessed by the user and the frequently accessed application, A_w

We apply the Naive Bayes algorithm formula to compute the application/s which has the highest probability of being accessed next by the user. To compute the probability of an application the following four attributes will be applied i.e. F_r, T_e, H_b, C_b . Simple ("naive") classification on method based on Bayes rule.

Bayes Theorem (3)

$$P\left(\frac{A}{B}\right) = P\left(\frac{B}{A}\right).P(A)/P(B) \tag{3}$$

Computing probability of the application messaging (4):

$$P(msg / F_r T_e H_b C_b) = P\left(F_r T_e H_b C_b / msg\right).P(msg)/P(F_r T_e H_b C_b) \tag{4}$$

Applying the Naïve Bayes rule dropping the denominator:

Probability of the application messaging is computed as shown in (5):

$$P(msg / F_r T_e H_b C_b) = P\left(F_r T_e H_b C_b / messaging\right).P(messaging) \tag{5}$$

CHAPTER SIX
APPLICATION PREDICTOR IMPLEMENTATION AND EVALUATION

6.1 System requirements

Android is a collection of open source software used in mobile devices. The Android SDK provides the tools and API necessary to begin developing applications on the Android platform using the Java programming language. Android provides users with the opportunity to build and publish their own applications by providing an open development environment. Android treats all applications (native and third-party) as equals. Therefore, having such an open development environment requires security measures to be taken in order to protect the integrity of the Android platform and the privacy of its users. The standard IDE for Android is Eclipse which gives a wide development environment. Android supports multitasking, so that the user can run multiple applications simultaneously, thus enabling the user to check his/her mail while loading other web page.

For the prototype and final prediction launcher, the following are the minimum system requirements;

6.2 Development

The minimum hardware and software requirements used for developing the predictor engine are as indicated in table 6.1. The operating system which should be installed on your desktop computer, the processor specifications, the RAM and the applications software that are necessary to develop android mobile application.

Table 6.1: Minimum development requirements

Requirement	Details
Operating System	Flavors of Windows NT, Linux or iOS
Processor	2.4 GHz or more
RAM	2 GB or more
Additional software	Java Compiler (Java™ 1.6 or higher recommended), Android SDK , Integrated Development Environment (IDE)

6.3 Implementation

The minimum hardware and software requirements for the implementation of the predictor engine is as indicated on table 6.2.The mobile device operating system should be Android 4.0 and the processor of 1Ghz or higher

Table 6.2: Minimum implementation requirements

Requirement	Details
Operating System	Android 4.0 or higher
Processor	1Ghz CPU or higher recommended

6.4 Application Training

The application training process is depicted on figure 6.1. The training begins with accessing the applications, assigning the apps timestamps, determining the application access frequency, and assigning true/false values for health and economic benefit. The values are collected in a knowledgebase from which the applications are classified for display on the predicted interface.

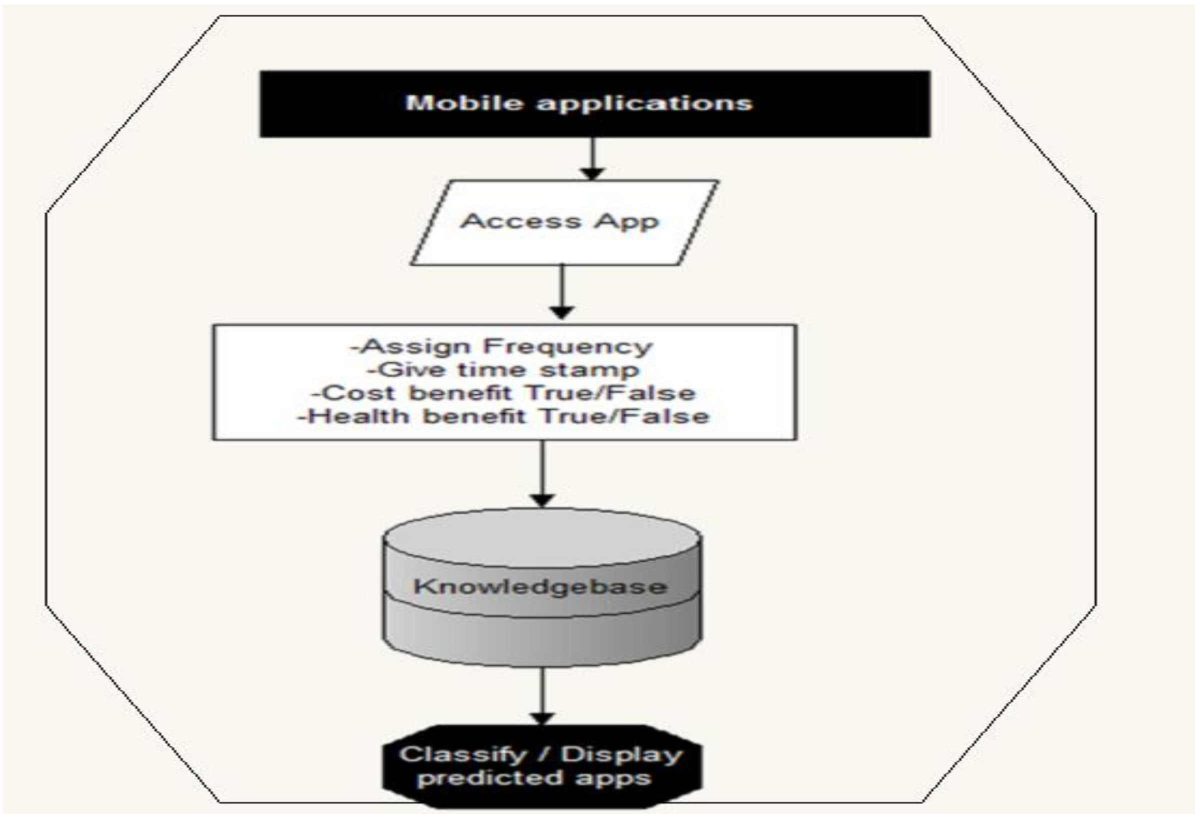


Figure 6.1: *Application training*

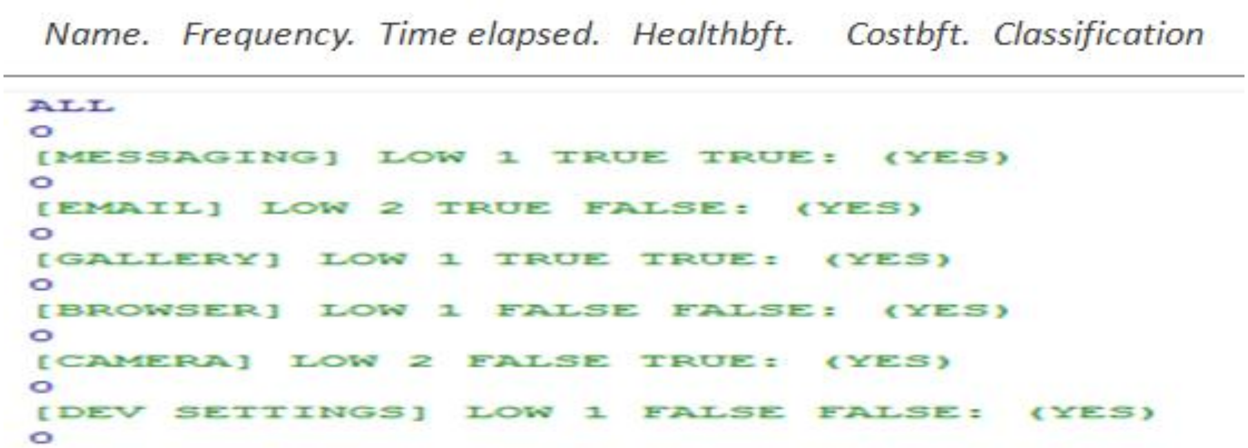
The data in Table 6.3 below represents the training data set that has been subjected to the naïve Bayes algorithm in order to predict the apps. After training based on the selected properties, an application is marked for display on the predicted interface or not with "Yes - No" values. All applications with a "Yes" value are bundled for display. The applications rated High represents the application that has been accessed more times compared to the rest, while low represents applications that have been accessed but not recently.

Table 6.3***: Application training data***

FREQUENCY	LAST_TIME _ACCESSED	HEALTHBENEFIT	FINANCIALBEBEFIT	SHOW
HIGH	0	TRUE	TRUE	YES
LOW	2	FALSE	FALSE	NO
HIGH	72	TRUE	FALSE	YES
LOW	5	TRUE	TRUE	NO
LOW	2	FALSE	TRUE	YES
HIGH	1	FALSE	FALSE	NO
LOW	3	TRUE	TRUE	YES
HIGH	12	FALSE	TRUE	YES
LOW	100	FALSE	TRUE	NO
HIGH	2	FALSE	FALSE	YES
HIGH	40	TRUE	FALSE	NO
LOW	4	TRUE	FALSE	YES
HIGH	4	FALSE	FALSE	NO

6.5 Application Prediction Output

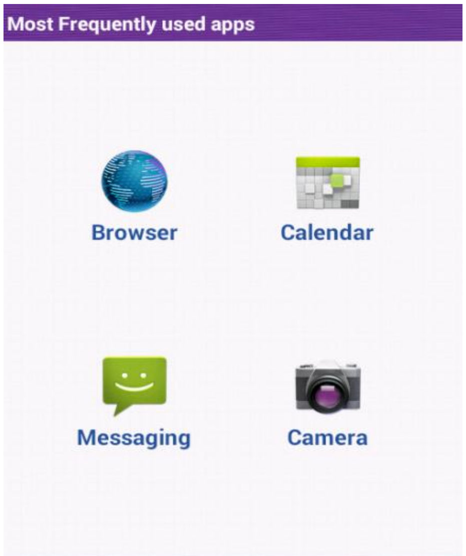
The sample application prediction data at time *t* which was captured is as shown in Figure 6.2. The data was collected on the frequency of access, time elapsed, health and economic benefit of the applications accessed.


Name. Frequency. Time elapsed. Healthbft. Costbft. Classification

ALL
O
[MESSAGING] LOW 1 TRUE TRUE: (YES)
O
[EMAIL] LOW 2 TRUE FALSE: (YES)
O
[GALLERY] LOW 1 TRUE TRUE: (YES)
O
[BROWSER] LOW 1 FALSE FALSE: (YES)
O
[CAMERA] LOW 2 FALSE TRUE: (YES)
O
[DEV SETTINGS] LOW 1 FALSE FALSE: (YES)
O

Figure 6.2: *Sample App Classification*

Figure 6.3 shows the most frequently accessed applications based on the training data.



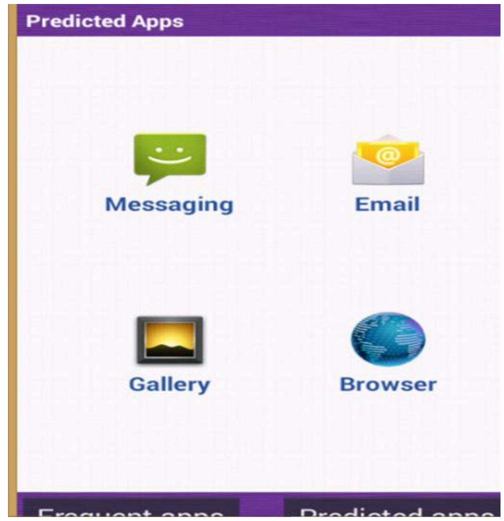


Figure 6.3: *Most accessed applications* ***Figure 6.4:*** *Predicted applications*

Figure 6.4 shows the first four predicted applications on the adaptive interface it corresponds to the sample (*Output A*) shown on *Figure 6.2* above at time t. The prediction is based on a combination of frequency of access, time intervals between access periods, health and economic benefit.

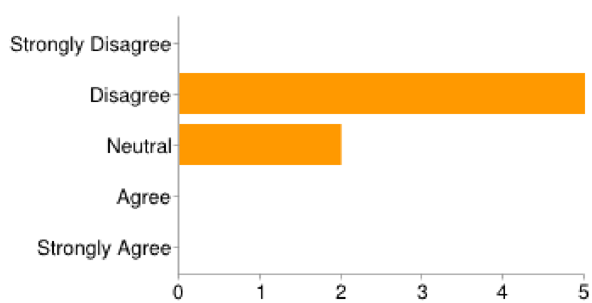
6.6 Application Evaluation

The application evaluation was conducted over a period of one and a half month. The process involved seven respondents who were part of the sampled respondents (elderly users) during data collection process and were using android mobile devices. The respondents were from Nairobi region and were randomly selected for the evaluation. The respondents were allowed to use the application for a period of four weeks and after completed an online questionnaire (Appendix 2) on their experience with the application.

The application evaluation was based on three aspects: interface presentation, navigation experience and overall satisfaction. Users were requested to install the application on their Android phone. Once installed, they interacted with other applications on their phones and after viewed the most frequently accessed and predicted applications using the application Predictor. A survey (Appendix 2) was then carried out to collect the user views. All respondents indicated interaction with their phones almost often. With the growth in adoption of technology, mobile phones have become part of our daily lives.

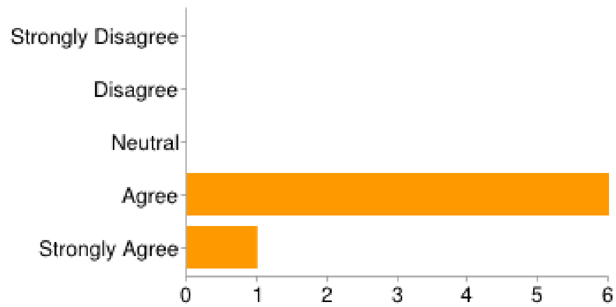
6.6.1 Interface Presentation

Respondents were asked to give their views on the existing interfaces and the predicted interface. The existing interfaces were rated unfriendly by 71% of the respondent (figure 6.5). However, with the interface predictor application, more than 86% of the respondents rated the interface as user friendly (figure 6.6). This is attributed to the fact that the predictor application tracks user applications based on frequency of use, health and economic benefits, simplifies the presentation and presents the user with an interface that is less crowded. The elderly users require there preferred applications prominently displayed on the home screens of their phones.



Strongly Disagree	0	0%
Disagree	5	71%
Neutral	2	29%
Agree	0	0%
Strongly Agree	0	0%

Figure 6.5: *User friendliness of existing interfaces*

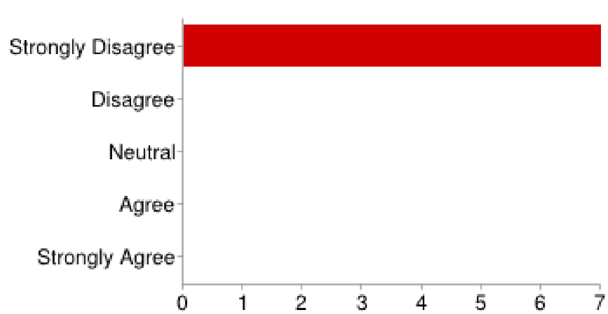


Strongly Disagree	**0**	0%
Disagree	**0**	0%
Neutral	**0**	0%
Agree	**6**	86%
Strongly Agree	**1**	14%

Figure 6.6: *Predictor application user interfaces*

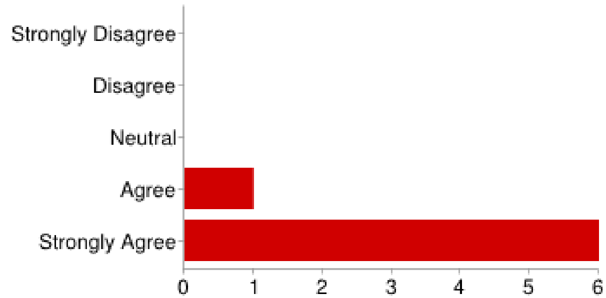
6.6.2 Navigation Experience

Navigation experience was evaluated with the ability of the interfaces to track most and frequently used applications. The current interfaces were rated not useful in aiding users to track frequently used applications (figure 6.7). The predictor application was rated highly for being able to aid users track most frequently accessed applications with a response rate of more that 83% (figure 6.8). This is attributed to the intelligence aspect incorporated into the application. This aids users and saves them on memory trying to recall applications commonly used. With more refinement, the application will go a long way in improving the user experience for the elderly phone users.



Strongly Disagree	**7**	100%
Disagree	**0**	0%
Neutral	**0**	0%
Agree	**0**	0%
Strongly Agree	**0**	0%

Figure 6.7: *Tracking most used applications for current interfaces*

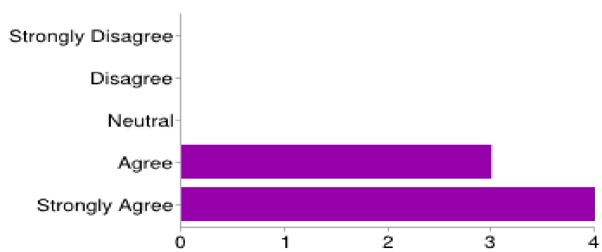


Strongly Disagree	**0**	0%
Disagree	**0**	0%
Neutral	**0**	0%
Agree	**1**	14%
Strongly Agree	**6**	86%

Figure 6.8: *Application Predictor tracking most used features*

6.6.3 Overall Satisfaction

More than 57% of the respondents were satisfied in using the predictor application for predicting display interfaces and also preferred to recommend the application for use by other elderly persons. Their general impression indicated that the predictor application was more helpful.



Strongly Disagree	**0**	0%
Disagree	**0**	0%
Neutral	**0**	0%
Agree	**3**	43%
Strongly Agree	**4**	57%

Figure 6.9*: Predicting display interfaces*

6.6.4 Summary

The elderly user rated the application predictor approach more user friendly since it made the navigation process easier. They were more satisfied because there was reduced memory work load since the predicted applications were fetched from their location to the predicted application interface. Navigation on a standard user interface user has to navigate across different screens to locate the application.

Comparison of User Interfaces

Figure 6.10 Standard mobile device UI

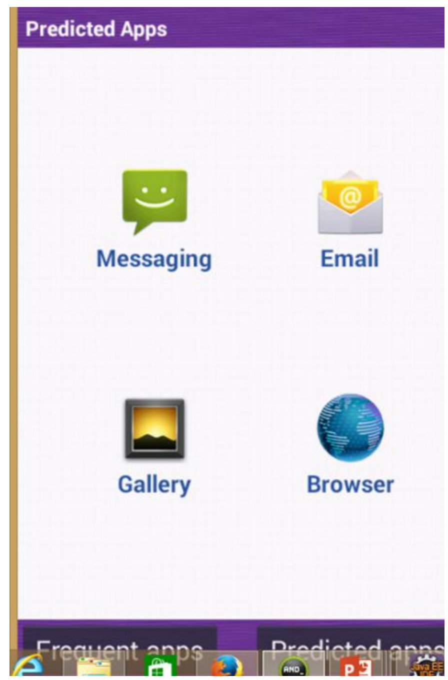


Figure 6.11 Simplified Adaptive UI (Predicted apps)

CHAPTER SEVEN

CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion and Recommendations

The dense increase in the number of applications installed in the mobile devices and their navigation by the elderly who might be facing declining capabilities as result of aging formed the focus of this research. The objective was to find out mobile device/s user interface navigation trends and experience by the elderly people and come up with an assistive technology to improve navigation and ease of use of mobile devices.

This study found out that a number of the elderly people are indeed experiencing some aging limitations mainly decline in vision ability and memory load resulting to challenges while accessing applications on their mobile devices. An Intelligent application predictor was developed to assist the users by predicting the applications that are most likely to be accessed and present them in a simplified user centric interface. The application predictor approach made the navigation process easier since the predicted application were fetched from their location to the predicted application interface compared to navigation on a standard user interface where user has to navigate across different screens to locate the application.

It is also recommended that collaborative research be done between mobile application firms, application developers and cognitive psychologists; this will help in informing mobile application developers and companies on the design philosophies for user interfaces to avoid blocking out people with limitations from using technology.

7.2 Areas for Further Research

Future work may aim at initializing the predictor at the applications launch phase rather than running it after interacting with the device.

Since this study focused on frequency of access, elapsed time between access periods, health and economic benefits of applications to predict the application accessed; future research may consider mapping the aging limitations with the apps that are best suited for particular age groups. Future research may additionally consider mapping the aging limitations with the apps that are best for this age group. Also, this research was based on the Android platform; future research can be extended to other platforms.

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APPENDICES

APPENDIX 1: Mobile Devices Navigation Study

MOBILE DEVICES UI NAVIGATION FOR OLDER ADULTS

Dear Respondent,

I am the undersigned, currently undertaking a Master of Science degree in Software Engineering at JKUAT. I am conducting a study involving collecting data for writing and compiling the final research thesis as a requirement for the award of the degree. The research entails mobile device interfaces; user interactions and experiences with those interfaces. The research seeks to conduct a survey on the user's views and experiences when navigating the mobile device interface applications with a focus on the older adults.

The information collected will be used solely for academic purposes and will be handled with utmost confidentiality.

Kindly fill in all the items on the questionnaire.

Please direct any enquiries to: Margaret Ngugi

E-mail magretr@gmail.com, Cell phone: 0720365551

Part 1: Demographic Information

Please check ☑ or write your answers to these questions appropriately.

1.1 Age: ☐ 45-50 years ☐ 50-55 years ☐ 55-60 years ☐ 60-65 years

1.2 Gender: ☐ Female ☐ Male

1.3 Highest level of education:

☐ Doctrate Degree ☐ Masters Degree ☐ Bachelors Degree ☐ Diploma

☐ Other (Specify) ………………………………………..

1.4 Employment status:

☐ Self employed ☐ Retired ☐ Employed ☐ Unable to work ☐

Other (please specify)…………………………………………………

1.5 Do you have any age-related limitations? (Limitation means something that prevents you from doing daily activities of living without assistance.)

☐ Yes ☐ No

1.6 If you answered 'Yes' to Q1.5, please indicate which of the following apply (mark all that apply to you).

☐ Decline in vision ability ☐ Hearing difficulty

☐ Limited hand movement ☐ Poor memory

☐ Others (please specify)

……………………………………………………………………………………
……………………………………………………………………………………
……………………………………………………………………

Part 2: Mobile Device User Experiences and Requirements

2.1 For how many years have you been using a mobile device?

☐ Less than 1 Year ☐ 1-5 Years ☐ 5-10 Years ☐ more than 10 Years

2.2 What type of mobile device are you currently using?

☐ Modern mobile devices (e.g. iPad, tabloid)

☐ Smart phone (e.g. android phones, windows mobile phones, iPhone)

☐ Internet enabled phones

☐ Typical mobile phone with keypad

2.3 How long did it take you to learn and use your current mobile device comfortably?

☐ Less than a week ☐ 1-2 Weeks ☐ 2-4 Weeks ☐ 1 Month ☐ More than one month ☐ Still Learning

2.4 Which of the following modes do you employ to gain familiarity with mobile device usage?

☐ Internet search

☐ Reading manuals

☐ Help from family or friends,

☐ Customer service assistance

☐ Self learning

☐ Using help menu

☐ Other ways (please specify)

…………………………………………………………………………………………

……………………………………………………………………………………

2.5 Do you face any challenges when navigating your mobile device interface?

☐ Yes ☐ No

2.5.1 Please rate your experience while using the following mobile device interface applications

Mobile device application	**Very simple**	**Simple**	**Fair**	**Difficult**	**Very Difficult**
2.5.1.1Phone calls	☐	☐	☐	☐	☐
2.5.1.2 Messaging	☐	☐	☐	☐	☐
2.5.1.3 M-Pesa/YUcash/ Airtel Money/Orange Money	☐	☐	☐	☐	☐
2.5.1.4 Internet access	☐	☐	☐	☐	☐
2.5.1.5 Games	☐	☐	☐	☐	☐
2.5.1.6 Calendar	☐	☐	☐	☐	☐
2.5.1.7 Clock	☐	☐	☐	☐	☐
2.5.1.8 Health updates	☐	☐	☐	☐	☐
2.5.1.9 Farming activity updates	☐	☐	☐	☐	☐
2.5.1.10News updates	☐	☐	☐	☐	☐
2.5.1.11Weather Updates	☐	☐	☐	☐	☐
2.5.1.12Browser	☐	☐	☐	☐	☐

Mobile device application	**Very simple**	**Simple**	**Fair**	**Difficult**	**Very Difficult**
2.5.1.13Downloads	☐	☐	☐	☐	☐
2.5.1.14Camera	☐	☐	☐	☐	☐
2.5.1.15Gallery	☐	☐	☐	☐	☐
2.5.1.16Radio	☐	☐	☐	☐	☐
2.5.1.17Email	☐	☐	☐	☐	☐
2.5.1.18Settings	☐	☐	☐	☐	☐
2.5.1.19 Other (Please specify)………………………………………………………………	☐	☐	☐	☐	☐

2.6 Which of the following is your most preferred icon layout on your mobile device? (Tick only one)

☐ List ☐ Grid ☐ Table format ☐ Image and Label

2.7 Which of the following icon sizes do you prefer?

☐ Small icons ☐ Medium icons ☐ Large icons

2.8 How many functions would you prefer to appear on the main screen of your mobile device?

☐ None ☐ 1-4 ☐ 4-8 ☐ More than 8

2.9 Please rate the importance of the following aspects related to usability of mobile devices

A mobile device interface should:	Not important	Quite important	Important	Very important
2.9.1 Be easy to learn and use	☐	☐	☐	☐
2.9.2 Be easy to read texts on the screen	☐	☐	☐	☐
2.9.3 Be simple	☐	☐	☐	☐
2.9.4 Be able to predict users frequently accessed applications.	☐	☐	☐	☐
2.9.5 Be able to monitor and predict application based on user's priority	☐	☐	☐	☐
2.9.6 Assist the user in memorizing frequently used applications	☐	☐	☐	☐
2.9.7 Be able to adjust to user's preferences	☐	☐	☐	☐
2.9.8 Be refined to ease navigation	☐	☐	☐	☐
2.9.9 Provide navigational support options for the elderly	☐	☐	☐	☐

2.10 Which of the following functions would you prefer using in navigating mobile device interface applications?

☐ Short cuts

☐ Voice activation

☐ Emergency call button (e.g. 911)

☐ Audio display: a function to read aloud menus and pressed keys

☐ Mobile device interface that displays frequently used applications

☐ Mobile device interface that predicts user's applications

☐ Adaptive mobile device interface

☐ Other ways (please specify)

………………………………………………………………………………………

…………………………………………………………………………

Thank you for taking your time to complete this questionnaire.

APPENDIX 2: Applications Predictor Evaluation Questionnaire

Dear respondent,

This study is meant to evaluate the developed predictive application against three aspects: Interface presentation, Navigation experience and overall satisfaction. You are first requested to install the application on your Android phone. Once installed, interact with the applications on your phone and then go to the Predictor application to view the most frequently accessed applications and the predicted applications for display on the home screen.

Please fill the questionnaire after interacting with the Predictive application. It will take approximately 7 minutes of your time.

Thank you for participating.

Please direct any inquiries concerning this survey to:

Please direct any enquiries to: Margaret Ngugi

E-mail magretr@gmail.com, Cell phone: 0720365551

1. Do you interact with your mobile device oftenly?

☐ Yes ☐ No

2. If yes in Q1, Please rate the extent to which you agree/disagree with the following statements in regard to your interaction with the user interface applications

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
The application representation was friendly	☐	☐	☐	☐	☐
The device interface was useful in tracking most frequently accessed phone features	☐	☐	☐	☐	☐
The device interface was able to predict correctly my preferred phone features	☐	☐	☐	☐	☐
The mobile device interface behaved intelligently	☐	☐	☐	☐	☐
I was pleased with presentation and would use it as my display interfaces	☐	☐	☐	☐	☐
I would recommend the application(s) to more users especially the elderly	☐	☐	☐	☐	☐

3. Please rate the extent to which you agree/disagree with the following statements in regard to your interaction with this predictive application.

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
The representation was friendly and interactive	☐	☐	☐	☐	☐
The application was useful in tracking most frequently	☐	☐	☐	☐	☐

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
accessed phone features					
The application was able to predict correctly my preferred phone features	☐	☐	☐	☐	☐
The application behaved intelligently	☐	☐	☐	☐	☐
I was pleased with the application and would use for predicting my display interfaces	☐	☐	☐	☐	☐
I would recommend the application to more users especially the elderly	☐	☐	☐	☐	☐

4. Please describe your general impression of the predictive application.
……………………………………………………………………………………………
……………………………………………………………………………………………
……………………………………….

Thank you for taking your time to complete this questionnaire.

APPENDIX 3: Naïve Bayes Predictor Implementation

```
public class Predictor extends AppWidgetProvider {
	public void onUpdate(Context context, AppWidgetManager appWidgetManager,   int[] appWidgetIds) {
		ComponentName thisWidget = new ComponentName(context, Predictor.class);
		int[] allWidgetIds = appWidgetManager.getAppWidgetIds(thisWidget);
		for (int widgetId : allWidgetIds) {
			RemoteViews views = new RemoteViews(context.getPackageName(),R.layout.main);
			Intent intent = new Intent(context, MainActivity.class);
			PendingIntent pendingIntent = PendingIntent.getActivity(context, 0, intent, 0);
			appWidgetManager.updateAppWidget(thisWidget, views);
		}
	}
}
```