# Design and Evaluation of a Predictive Model for Smartphone Selection

Yerika Jimenez and Patricia Morreale

Department of Computer Science, Kean University 1000 Morris Ave, Union, NJ 07083, United States {jimenyer,pmorreal}@kean.edu

**Abstract.** Selecting a mobile phone is a very subjective process; consumers often base their decisions on advertising and their personal expectations for the device. In order to provide consumers with simpler and more objective information, a predictive model for smartphone selection has been developed. Four of the most popular mobile devices were used for the development of this model: Apple's iPhone, Google's Android, Microsoft's Windows and Research In Motion's BlackBerry. Everyday tasks, common to smartphone users, were identified and modeled, using the Keystroke Level Model. Fitts' Law was used to provide additional objective data based on the dimensions and layout of the mobile phone screen. These objective measures were integrated with user preferences, to identify which smartphone would provide superior operation and performance for the features most desired by the smartphone consumer. Research outcomes from this project include the identification of the mobile devices that performed common tasks with efficiency and a user-task model predicting user smartphone selection based on individual utility and task frequency.

**Keywords:** Keystroke Level Model (KLM), Fitts Law, Human Factors, Mobile Devices, And Human Computer Interaction Factors.

#### 1 Introduction

A predictive model for smartphone selection uses human computer interaction (HCI) factors as well as personal preferences to identify the smartphone best suited for an individual. Consumers are overwhelmed by the range of price points and the variety of handheld mobile devices, particularly in the subclass referred to as smartphones. Given the availability of a wide variety of mobile phones, individuals are faced with the task of choosing between phones with often minimal understanding of various features of the mobile device. For this reason, a predictive model was created in order to make the consumer smartphone selection experience less stressful and more informed by knowledge. To accomplish this, a Keystroke Level Model (KLM) was developed by identifying the basic interaction elements for smartphones and estimating the expected user performance for everyday tasks. This paper will focus on time and performance predictions for each smartphone.

# 2 Experimental Design

The experimental design of the project included four parts. First, an online survey was conducted to find out how the general consumer population regards their mobile devices. Using their answers, a predictive model was created to determine the best mobile device for an individual. Based on the answers provided by consumers in the survey, five of the most popular mobile devices were chosen, which were identified as serving the majority of mobile smartphone consumers: Blackberry, Android, iPhone, Windows phone and Sidekick 4. Next, a Keystroke Level Model (KLM) was designed that provided a breakdown of each keystroke used by each user and comparatively identified the time needed by each mobile device to perform each assigned task. Each task was assigned an individual keystroke base on the KLM standards operations, measured in seconds. Fitts' Law was used to measure how much area each icon took up on the screen display and to find out how much time it will take a user to locate an icon and how big the icon is. Finally, a predictive model was created with the information gathered from the user survey, KLM task assessment and physical measurement.



Fig. 1. Experiment Design Components

## 3 Related Work

This paper uses Keystroke Level Model (KLM) time specifications for existing operators for comparison of results and estimating how much time each routine task requires when performed. KLM has been shown to predict skilled use of desktop systems, but has not been validated on a handheld device that uses a stylus instead of a keyboard [1]. Research has found that KLM accurately predicts task execution time on handheld user interfaces with less than 8% prediction error.

Most research on performance measurement of phone users has been limited to the measurement of input of text for short messages. An initial work by Dunlop and Crossan [2], shows KLM operator sequences for three different text entry methods: traditional, predictive and word completion. However, the authors adopted the original operator values used for desktop interaction, which proved to be imprecise in the environment studied here. Although this paper does not focus on text messaging, it does provide measured approximations for real user behavior with text entry. Some models can correctly predict which input method is faster than others. More research has been done on reporting measurement times for key presses and the mental act operator for text input in different languages [3].

Additionally, a text input study has shown how the time values of the original KLM operators apply to mobile phone menu navigation and concluded that the operator values fit quite well and suggested only minor modifications [4]. There is no published research that includes new mobile interaction techniques in its model. There are several possible approaches for the effectiveness of predictive models that are relevant to a single instance. One approach is to learn a model from a subset of the training data set that consists of instances that are similar in some way to the instance at hand. Another approach is to learn a model from a subset of variables that are pertinent in some fashion to the instance at hand. A third approach, applicable to model averaging where a set of models is collectively used for prediction, is to identify a set of models that are most relevant to prediction for the instance at hand [5].

## **4** Mobile Device Specifications

Figure 2 shows an overview of the specification of each mobile device used in this project. Only four of the smartphones listed below were used. Unfortunately, due to a lack of popularity identified in the initial online user survey, the Sidekick 4 was removed from the project. The operating system for each mobile device was essential because it shows the differences between the smartphone models. Figure 2 also shows the dimensions, weight, keyboard design, and physical appearance in a comparative fashion of the selected phones.

Smart Phone	Blackberry Bold 9700	iPhone 4 & 4s	Galaxy's Nexus	Sidekick 4	Nokia Lumia 900
Operating System	Blackberry OS	Ios	Android	Hiptop OS	Windows Phone 7.5
Dimension Weight Keyboard	109 x 60 x 14 mm 122 g QWERTY	115.2 x 58.6 x 9.3 mm 140 g Touch-sensitive	135.5 x 67.9 x 8.9 mm 135g Touch-sensitive	127 x 61 x 15 mm 162 g QWERTY	116.5 x 61.2 x 12.1mm 142 g Touch-sensitive
Physical Appearance					U # 52
Manufacturer	Research in Motion (RIM)	Foxconn	Samsung	Danger Incorporated, Sharp, Motorola, Samsung	Nokia
Carrier	T-Mobile, AT&T, Sprint, Verizon	AT&T, Sprint, Verizon	Sprint, Verizon	T-Mobile	T-Mobile, AT&T, Sprint, Verizon
Speed	4G	4G	3G/4 G	4G	4G

Fig. 2. Mobile device specifications

## 4.1 Human Computer Interaction Factors

This research used various types of Human Computer Interaction (HCI) factors. Usability for the online survey was provided by Quatrics. The online survey was distributed to university staff and students. A total of 100 responses were received, in which 22% were male and 78% were female. The ages ranged from 18 to 56 years old.

## 4.2 Task Completion

Keystroke Level Model (KLM) was used to determine which mobile device could perform a task the fastest. A series of four tasks that every mobile device holder does regularly was created. The tasks used were the following:

- 1. Add a contact
- 2. Compose a text message
- 3. Change a ringtone
- 4. Search for a contact

Five participants owning the specified mobile device performed each task. Figure 3 shows a female user performing the task for the mobile device Android.



Fig. 3. Female user performing KLM task

## 4.3 Physical Layout

The physical layout portion of this research was to measure in millimeter (mm) the dimensions of the total screen area for each of the four mobile devices. The dimensions of screen icons on the display screen were also measured. The purpose of this effort was to find out how much time was needed by the user to locate an icon and how big the icon is.

# 5 Keystroke Level Model (KLM)

The Keystroke Level Model (KLM), created by Card, Moran, and Newell in 1980 [6] is an established measurement norm in HCI. KLM is a simple but accurate means to produce quantitative information, an objective prior prediction of task execution time at an early stage in the development process [1]. The main purpose of KLM is to accurately predict task execution time for mouse-and-keyboard (point-and-click) systems. Middle-sized touch screens are becoming much more popular so it is important to determine whether KLM can provide useful predictions for these interfaces as well [7, 8]. The KLM describes task execution in terms of four physical-motor operations: **K** (key-stroking), **P** (pointing), **H** (homing), **D** (drawing) and **M** (mental preparation). Responses must be estimated by the analyst and only include the time that the user must wait for the system after any **M** operator has been completed [1].

## 6 Fitts' Law

Fitts' Law is mostly frequently used in interface design and in attempts to create user-friendly environments. Fitts' Law describes the time needed to move from one point to another, given the characteristics of the target device. Both device or screen width and amplitude play a large role in the Law. Fitts' Law is a one-dimensional model of human movement, which is commonly applied to two dimensional target acquisition tasks on interactive computing system [9, 10].

# 7 User Survey

As stated in section 4.1, an online survey was distributed to the online community of university staff and students. A total of 100 responses were received, of which 22% were male and 78% were female. The ages of survey respondents ranged from 18 to 56 years old. The purpose of the survey was to find out how much the general population knows about their smartphones. Figure 4 demonstrates the user responses when asked if they knew what operating system their mobile device used. Only 47% of the participants knew the operating system of their smartphone. This shows that users do not always know what components or features are available in their smartphone.

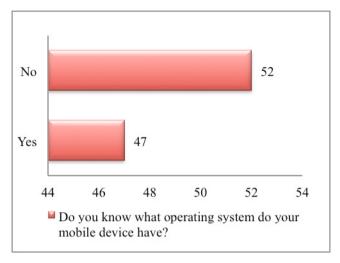


Fig. 4. Smartphone User Survey Question

## 8 Keystroke Level Model (KLM) Task Identification

As mentioned in section 4.2, KLM was used to determine which mobile device could perform the selected tasks faster. Tasks were broken down using KLM standard times for each of the tasks. As stated in section 5, there are four physical-motor operations; for this research only three were used. A single keystroke was used to represent a step from each task.

- **K** Represents pressing or clicking a key or button (.20 seconds)
- H Represents moving the hands to the keyboard location (1.0 seconds)
- **M** Mentally preparing for the task.

At times operations were concatenated and repeated. T10K or T4K means Mental preparation, then 10 Key presses (T4K = 1.5 seconds) and (T10K = 5.5 seconds). Table 1 is an example of how the keystrokes were broken down.

Add a contact					
Blackberry					
Description	Operation	Times in seconds			
Place MD in vertical position	H (home screen)	1.0			
Move hands to keyboard	H (keyboard)	1.0			
Press menu	K (keyboard)	.20			
Press contacts	K (screen)	.20			
Press " New contact"	K (screen)	.20			
Type name	M4K (word)	1.5			
Type number	M10K (10 digit number)	5.5			
Press save	K (keyboard)	.20			
TOTAL:	9.8 seconds				

Table 1. Blackberry KLM Task

# 9 KLM Data Gathering

Table 2 illustrates the time taken for each task to be completed by the participants performed when using their personal devices. Only the standard KLM metric was used for this comparative assessment, although there are specialized application metrics available for some of the devices used in this study [11]. As shown in the table, the iPhone can execute the task to add a contact in only 8.4 seconds. However, the Android executes the next three tasks using the least amount of keystrokes, measured in seconds. An interesting observation in Table 2 is that about the same number of keystroke were use for Android and Windows smartphones in task number one ("Add a contact") and task number three ("Compose a text"). It can be inferred that the Android operating system (OS) strives to execute tasks faster than any other OS. Many people are surprised by this outcome as the iPhone is very popular with consumers, leading to a perception that the iPhone performs tasks faster than other smartphone models. This research identified that the iPhone is not the fasted smartphone device available to consumers, based on actual user measurement of comment tasks using standard HCI evaluation tests.

KLM	Blackberry	iPhone	Android	Windows
Add a contact Change ringtone	9.8 sec 12.4 sec	8.4 sec 6.6 sec	8.6 sec 5.2 sec	8.6 sec 6.6 sec
Compose a text	9 sec	8.6 sec	8.4 sec	8.4 sec
Search a contact	5.1 sec	2.7 sec	2.5 sec	2.9 sec

Table 2. KLM task measurement, in seconds

## 10 Fitts' Law Component

Table 3 represents the total display surface area for each of the four mobile devices. Each icon was measured to determine the amount of space occupied by the icon on the display screen, the distance between the centers of the icon and position of the icon on the 1<sup>st</sup> screen, 2<sup>nd</sup> screen, or later screens. The purpose of this objective measurement was to find out how much time was needed by a user to locate an icon and how big the icon is. As shown in Table 3, the Android has a display area of 44.36 mm; this makes the Android screen have a picture-perfect proposition.

Fitts' Law	Blackberry	iPhone	Android	Windows
Total area of display (mm)	19 mm	37. 50 mm	44.37 mm	48.36 mm
Total space used by welcome screen icons (mm)	.49	.72	.20	.48
Screen center to icon	4.2	6.8	9.5	0
Is a 2 <sup>nd</sup> screen needed to access icons?	Yes	No	Yes	Yes
Number of icons on first screen	6	16	4	7

Table 3. Fitts' Law Assessment

## 11 Predictive Model

Based on user responses on the survey and the tasks performed on each of the mobile devices, a predictive model was developed to provide consumers with additional information and to make the user experience stress-free when picking a new smartphone. As the Fig. 5 indicates, a user must know the primary function they plan to use on their mobile phone. Depending on their answers to the model, different features and specifications will be input for the final recommendation.

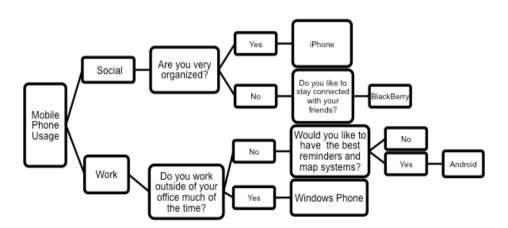


Fig. 5. Predicted model flowchart

## 12 Future Work

This research is continuing. More KLM tasks are be performed with the same smartphone models for more accurate predictions. A website is being created to help users pick smartphones with confidence and ease. The researchers are expanding the predictive model to include additional research results, such as the performance of smartphones on carrier networks [12] and with specific applications.

## References

- Luo, L., John, B.: Predicting Task Execution Time on Handheld Devices Using the Keystoke-Level Model. In: Conference on Human Factors in Computing Systems (CHI 2005), pp. 1605–1608. ACM, New York (2005)
- Dunlop, M.D., Crossan, A.: Predictive Text Entry Methods for Mobile Phones. Personal Technologies 4, 2–4 (2000)
- 3. Myung, R.: Keystroke-Level Analysis of Korean Text Entry Methods on Mobile Phones. International Journal of Human-Computers Studies 60(5-6), 545–563 (2004)
- 4. Mori, R., Matsunobe, T., Yamaoka, T.: A Task Operation Prediction Time Computation Based on GOMS-KLM Improved for Cellular Phone and the Verification of the Validity. In: Proceedings of the Asian Design International Conference (2003)
- Visweswaran, S., Cooper, G.: Learning Instance-Specific Predictive Models. Journal of Machine Learning Research 11, 3333–3336 (2010)
- Card, S.K., Moran, T.P., Newell, A.: The Keystroke-Level Model for User Performance Time with Interactive Systems. Communications of the ACM archive 23(7), 396–410 (1980)
- Abdulin, E.: Using the Keystroke-Level Model for Designing User Interface on Middle-Sized Touch Screens. In: Conference on Human Factors in Computing Systems (CHI 2011), Vancouver, BC, Canada, pp. 673–686 (2011)
- 8. Holleis, P., Otto, F., Hussmann, H., Schmidt, A.: Keystroke-level Model for Advanced Mobile Phone Interaction. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2007), pp. 1505–1514. ACM, New York (2007)
- MacKenzie, I.S., Buxton: Extending Fitts' Law to Two-Dimensional Tasks. In: Proceeding of the CHI 1992 Conference on Human Factors in Computing System, pp. 219–226. ACM, New York (1992)
- MacKenzie, I.S.: Fitts' law as a research and design tool in human–computer interaction. Human–Computer Interaction 7, 91–139 (1992)
- Castellucci, S., MacKenzie, I.S.: Gathering Text Entry Metrics on Android Devices. In: Extended Abstracts of the ACM Conference on Human Factors in Computing Systems (CHI 2011), pp. 1507–1512. ACM, New York (2011)
- Huang, J., Xu, Q., Tiwana, B., Mao, Z., Zhang, M.: Anatomizing Application Performance Differences on Smartphones. In: Proceedings of the 8th International Conference on Mobile Systems, Applications and Services (MobiSys 2010), pp. 165–170. ACM, New York (2010)