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Research Paper

Demographic Analysis of Smartphone Application Usage Related to eHealth

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ABSTRACT:*Smartphone application usage according to battery percentage was examined with 68 participants. A one way chi square test found that there was a pattern with participant's application usage that couldn't have been due to chance alone, meaning that users consumed more battery for certain applications in a twenty four hour time span, over other applications. A one way chi square analysis also indicated a preference of iOS devices over android ones within the female gender. A frequency analysis also indicated that only one user had a health application as his number one used app according to battery consumption, while only two users out of 68 had any sort of health application usage at all. Results from analyzing user's battery consumption suggest a lack of health application usage on mobile devices*

Keywords:*Mobile, eHealth, Smartphones, Software, Demographics*

I. INTRODUCTION

Health applications have come into the domain of mobile phones, and with other research studies in the scientific literature focusing on developing effective health care treatment delivery services via software applications, the need for more research is omnipresent [1,2,3,4,5] Multiple important organizations, such as the World Health Organization (WHO), have performed studies examining mobile health applications that examine general health problems, like cardiovascular risk [2].Other health applications that focus on specific medical issues, like diabetes and chronic diseases, have come into the forefront of the healthcare industry [1,3].Furthermore, the studies that have taken place regarding mobile health applications have been a recent phenomenon, with the oldest cited reference in this paper dating back as recently as 2011 [6]. Studying mobile applications in general, and not just health applications, might lead a way into improving general interfaces for software applications. By studying possible gamification improvements in general applications, extrapolation to how health applications should be designed is plausible [6]. Furthermore, by understanding the demographics of users who use mobile applications, and studying how users interact with these services, development for improved Graphical User Interfaces (GUI's) can be accomplished, which have the potential to revolutionize how humans keep track of their health.

The need for user experience research with health and medical mobile applications has increased recently – as Martinez-Perez states [4]:

"The number of mobile clinical decision support applications and their inclusion in clinical practices has risen in recent years. Developers, however, must be careful with their interface or the easiness of use, which can impoverish the experience of the users"

Martinez-Perez [4] specifically refers to the user experience in his paper, which suggests that overall, human centered design approaches for improving interfaces need to be implemented. In order for human centered design to function, however, demographic information for establishing a target market needs to be established first.

Health applications have been developed before by the World Health Organization (WHO), that have shown to attract users. As Ordóñez&Tajer noted in 2015 [2]:

"... called the Cardiovascular Risk Calculator, it is based on WHO risk tables and applied to the countries of the Region... Four months after its launch, the application was being used daily by more than 12 000 users and had been downloaded in virtually all the countries of the region"

If 12,000 users were able to successfully download a health application for usage, then the probability of recruiting participants for a study regarding their demographic information is very likely.

The use of mobile health applications could have a profound impact on managing patients' health. By creating an application that can allow patients to keep track of their treatment progress, researchers were able to successfully improve the wellbeing of one patient during a pilot study. In 2015 Barr et al [1], showed with one participant, that health applications have been noted to encourage greater patient involvement with care, which has in turn been associated with better health outcomes. Although results from the larger real scale study associated with n=200 participants still needs to be reported, the pilot study shows the possibility of improving health user's medical wellbeing.

To collect demographic information on users, it's important to understand that there are different types of mobile health applications. These different types of mobile health applications often perform different functions, which might attract different demographics. A study by Huckvale et al [3] focused on a specific medical application that is meant to treat a specific disorder, rather than focusing on a general health/exercise application. It has been found that a significant amount of users have health applications on their smartphone, Huckvale et al stated [3]:

"forty two percent of US adults have a phone with one or more application and almost a third of these report having an app to help track or manage their health".

With fourteen percent of the United States population of smartphone users possessing a health application, the potential for utilizing those applications is significant. There's also a possibility to deliver scalable options for patients undergoing self-management, which the researchers articulate in their article [3]. Since a sixth of U.S. adults have mobile phone applications for health, recruiting participants for a health application study in general should be feasible.

Currently, applications for medical use are flawed and need to be revised. For example, handling patients with serious debilitating diseases is an arduous endeavor, which has to be precise. In a study that evaluated insulin calculators in mobile applications for patients with diabetes, researchers found that all except one application was accurate in assessing the appropriate dose for users. Huckvale et al reported [7]:

"Only one app, for iOS, was issue free according to our criteria. No significant differences were observed in issue prevalence by payment model or platform".

Researchers found that most current payment models or platforms don't need to be modified [7]. Payment models refer to the type of payment plan users have to pay for healthcare related costs, and platforms are referring to the type of system used to access the application. Since payment models have no bearing on whether the application is effective in calculating insulin doses for diabetic patients. Further modification of health applications for human use needs to occur in order for mobile devices to be an effective medium for delivering healthcare services.

Studying user experience design for a specific type of product involves doing demographic analysis, so that the best possible GUI can be built. Anderson et al recommend [5]:

"Understanding the range of consumer experiences and expectations can inform design of health application to encourage persistence in self-monitoring"

In the study performed, researchers found that getting user feedback from participants was one of the best way to design better health applications [5]. From medical applications that deliver health care treatment services to general health/exercise applications that record data users input, observing the user experience is a quintessential part of redesigning mobile health application. Other studies have suggested that current mobile health applications are designed poorly, which suggest that redesigning these applications are vital to the success of self-management care [7].

Gamification techniques for mobile applications were observed by Zichermann et al[6]. By using general concepts designed for mobile applications, understanding how health applications should be designed is possible. In user interface design, human centered research dictates that developers need to take into account demographic information for optimal user experiences. Furthermore, because research regarding mobile health applications is new, the study presented in this paper intends to analyze how users' demographic information predicts mobile application usage. Since demographic information is essential to understanding how applications should be designed, the following study will measure race, age, gender, and socioeconomic status. These demographic factors will be studied alongside participants' mobile application usage, which will unveil users' behavior regarding mobile health applications.

Since previous research has stated that improvements needs to occur in order for better health applications to developed, demographic information shall be collected. In human centered/UX design, methodology dictates that in order to do testing on users, their demographic information needs to be established first. The study being presented wishes to collect demographic information so that future designers have a target user group to recruit. The following study wishes to test these several hypotheses related to the prior research performed:

- **H1:** Participants socioeconomic status will significantly differ depending on what type of smartphone application they use most frequently.
- **H2:** As participant's age changes, so will their mobile smartphone application behavior.
- **H3:** Participants race will not significantly differ depending on what type of smartphone application they use most frequently.
- **H4:** Participants gender will not significantly differ depending on what type of smartphone application they use most frequently.

The hypotheses that are being presented are for setting a baseline to allow a comparison of the data. Previous research on demographic information related to health applications is limited, so these formulated hypotheses serve more as a criterion to contrast the data more so than to set a hard educated guess on what the data is going to look like. The goal of the study is to establish a demographic for health users, any sort of demographic at all, since the realm of mobile health applications is so new.

II. METHOD

This section will describe the participants, the materials and the procedure undertaken to complete the experiments required for this project.

Participants

Eighty five total participants were recruited. Out of the eighty five total participants, sixty eighty answered as being valid and having smartphone application usage. Thirty eight of the participants identified as being a male, while twenty nine identified as being a female, and one participant didn't specified gender. Out of the sixty eight participants, sixty five answered the age question, having a mean age of 25.66. Participants that were recruited had a smart-phone that records the amount of battery usage for each application they use. Valid participants smartphone were either iOS or Android, participants with non-smartphones were sorted out of the application usage analysis, since health applications aren't typically developed on non-smartphones. Out of sixty eight participants who recorded their smartphone application usage, forty had an IP address that originated from NY, while twenty three had addresses that originated in the United States outside of NY, and five had addresses outside of the United States (Figure 1).

Materials

A survey, developed to record the amount of hours/battery percentage users consume with their smartphone on a daily and weekly basis, along with demographic questions, was developed on qualtrics.com, using SUNY Oswego's license. Facebook and social media platforms were implemented to recruit participants of different demographic standing.

Smartphones were the main method to track users' health application usage, along with other software that they use on their phone. Participants with Android or iOS devices were able to access their battery percentage usage for applications that they've used. After selecting and finding the battery percentage usage for applications, users were then asked to put those applications in a list from greatest to least for their top ten most used applications.

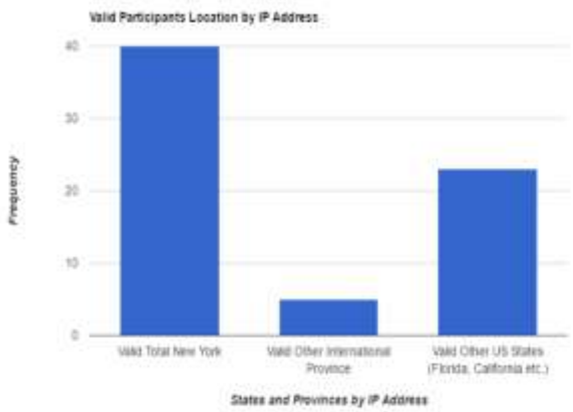

Fig 1. Participants Location based on IP Address

Procedure

Participants were recruited from various social media platforms in order to obtain a wide sample of demographic data. These social media platforms include Facebook and GroupMe. Use of an anonymous link from other non-social media platforms, such as email, was also used as a means to sample participants. Upon entering the website with the questionnaire, participants were asked to answer the questions in the survey. The survey asked users about their top ten most used application on their phone by battery consumption. To do this, users were prompted to go to “Settings” on their smartphone and then proceed to “Battery” where the interface would show them the most used smartphone application on their phone by battery usage. Participants with iOS devices were told to read one section of directions for finding battery percentage usage, while Android users were instructed to view a different part of the directions, since both had different interfaces and navigations. Furthermore, iOS devices listed the top ten applications on the phone within a 24 hour time span as well as a and seven day time span, while Android only kept track of battery consumption since last charge. Since there is a discrepancy in how the two different phones keep track of battery consumption, only the 24 hour list from (iOS devices) and last charge lists (from Android users) shall be compared together. Other information on the survey included a question about how old the participants were, as well as other demographic information such as race, income, and gender.

Questions that asked participants about their platform device were also included, as well as questions about the participant’s smartwatch usage. The question related to smartwatch usage asked participants what they used the smartwatch for, how many hours per week they used it, and how frequently they felt that they interacted with the watch. The IP addresses of participants were also recorded as a means to locate where users took the survey from. Participants were also asked if they were pregnant, as the National Institute of Health guidelines for human subject research dictates that pregnant women are to be given special considerations. After completing the questionnaire, participants were shown a debriefing form that they could read to understand the full scope of the study. This included information about the proposed research question related to smartphone application data and demographic information. It also included the researcher's phone number and email address, which the participant could decide to contact. The selection of a “check mark” box right next to “Accept” at the bottom of the survey, which is where the IRB form was, indicated that the user had read the form, giving consent, which allowed participants data to be used in an empirical setting. The consent form specifically refers to how each participant would be anonymous during the analyses, and they wouldn’t be coded in the database by their name. It also specifies how to contact the researchers, much like the debriefing form. It also included information on where to go if the participants felt like the study has had a detrimental effect on their mental wellbeing.

III. RESULTS

To test the first hypothesis, to see if it is possible to predict users socioeconomic status based on smartphone application usage, a 3x5 two way chi square analysis was performed with different income scales and three chosen smartphone applications (Facebook, Snapchat, Pokemon Go). Results indicated no significant differences, and that S.E.S. can’t be predicted based on smartphone application usage

$$X^2 (8, N = 15) = 5.28, P.N.S. \quad (1)$$

To test the second hypothesis, to see if it is possible to predict users age based off smartphone application usage, a one way between subjects Analysis of Variance (ANOVA) was performed with three groups (Facebook, Snapchat, Pokémon GO). Results indicated that there was no significant differences with age between the three groups

$$F(2, 18)= .513, P.N.S. \quad (2)$$

To test the third hypothesis, to see if it is possible to predict users race based on smartphone application usage, a two way chi square test would’ve been performed. It wasn’t performed, however, because there wasn’t enough of a diversity of races that took this survey (Figure 2).

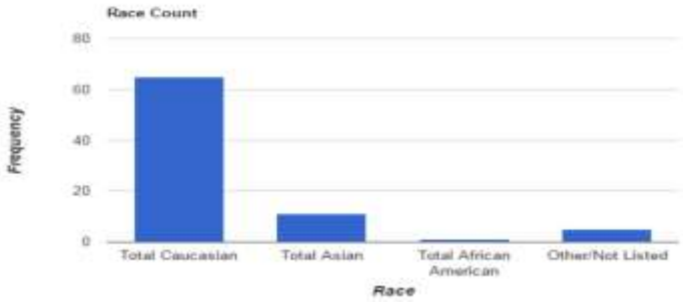

Fig 2. Participants' Self-Identified Race

To test the fourth hypothesis, to see if it is possible to predict users' gender based on smartphone application usage, a 2x20 two way chi square test was performed with twenty of the top applications used and the two genders recorded (male, female). Results indicated that the null hypothesis should be retained and that there was no preference in application usage based on gender

$X^2 (22, N = 68) = 21.85$, P.N.S.

(3)

The results from a one way chi square analysis showed that participants Frequency observed (Fo) for each different application could not be due to chance alone, and that there is a higher probability users will have more battery usage for certain applications over others (Figure 3).

$X^2 (22, N = 68) = 69.98, p < .01$

(4)

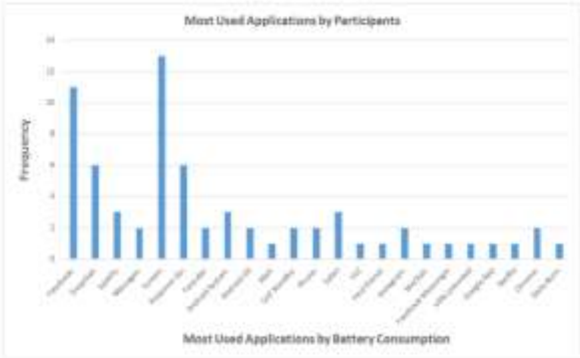

Fig 3. Participants' Most Used Applications by Battery Consumption

A one way chi square analysis also indicated a preference of iOS devices over android ones within the female gender (Figure 4)

$X^2 (1, N = 36) = 4.00, p < .05$.

(5)

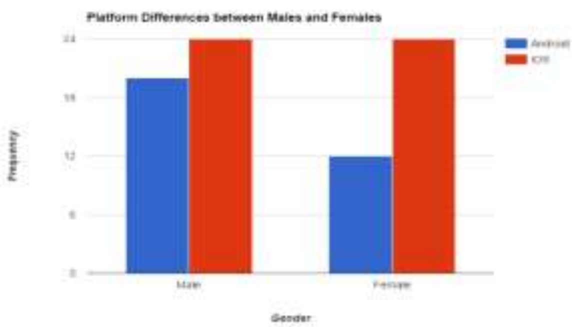

Fig 4. Participants' Smartphone Platform by Gender

It was also found that out of the sixty eight valid participants, eighteen were considered valid smartwatch users

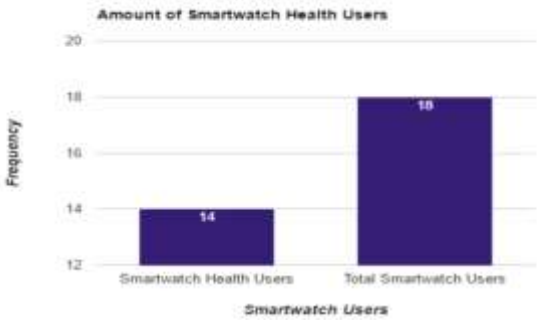

Fig 5. Amount of Smartwatch Users for Health

Out of these eighteen smartwatch users, none were recorded as having used a health application on their smartphone within the last twenty four hours or last battery charge (Figure 5).

IV. CONCLUSION

Results from the two significant analyses suggest a pattern with user's smartphone application behavior. Only one participant was recorded as having a health application (DailyBurn) as his top application used according to battery consumption. Battery consumption refers to the amount of battery the smartphone has used for a particular application. Out of the forty one valid iPhone users, none were found to use the health application that comes with the iPhone on their top ten used applications by battery consumption. The amount of usage recorded from participants with the iPhone's default health application suggests that the application is not ubiquitous. No iPhone users interacted with the health application enough on their phone for it to be reported on their top ten most used application by battery consumption. This might indicate that the sample collected either doesn’t know about the default iPhone application or doesn't prefer/interact with it enough for it to drain the battery. Furthermore, only two health applications in general have been reported in users top ten list (DailyBurn and Mapmyrun). This lack of application usage across sixty eight participants suggests that users don’t interact with health applications on their mobile devices frequently, especially with the default iPhone application. Proposing a business plan to Apple on how to improve their health application for users might be an avenue for generating new revenue, since none of the users have engaged with the application enough for it to appear on their top ten list. Furthermore, since results from the one way chi square test suggest that Facebook is significantly the most consumed application by users, it might be beneficial if Apple integrated Facebook into their health applications.

Out of the eighteen total valid smartwatch users, fourteen of them use their smartwatch for health related activities. This data indicates, along with the conjunction of data previously stated, that users don’t interact with health applications on their mobile phones. This might indicate that smartwatch users view their health application on their smartwatch rather than on their smartphone. It could also indicate that users interact with their health data on other devices, such as PC or tablet.

Further research into the topic of eHealth smartphone applications should be done by scientists/medical professionals looking to understand how users interact with eHealth systems. Although the research that was undertaken analyzed both quantitatively and qualitatively user's smartphone application usage, the study was not funded. All of the recruiting that was done to find participants was done by one graduate student, who didn’t use any money at all for the empirical research performed. Future studies need research grants to recruit a larger pool of participants so that more statistical inferences can be drawn and then compared to the current study presented. Furthermore, more data needs to be collected from participants so that variables such as participants’ health status can be studied. The array of questions were designed to be minimal for the participants to complete. This is because the dropout rate for the survey wanted to be minimized; participants had no incentive to complete the survey, so making the survey as user friendly and concise as possible needed to be done. If participants in future studies were motivated to complete the survey for a monetary reward, researchers would be able to put together a more sizable collection of questions to collect more data. Researchers in the future could also expand the scope of the study, and could look at other devices that contain health related applications/software. Tablets, desktop, laptops, along with other devices could be included in the study. More objective data regarding smartwatch applications could also be analyzed instead of self-reported data; much like how smartphone application usage was collected in the current study presented, smartwatch data should be collected in a similar fashion.

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