International Journal on Engineering Technologies and Informatics

Application of Artificial Intelligence and Data Science in Detecting the Impact of Usability from Evaluation of Mobile Health Applications

Research Article

Volume 5 Issue 1- 2024

Author Details

Olamide J Kayode[1], Tareq Al Jaber[2] and Neil Gordon[2]*

[1]Data Science, University of Hull, UK

[2]School of Computer Science, University of Hull, UK

*Corresponding author

Tareq Al Jaber, School of Computer Science, University of Hull, Hull, HU6 7RX, UK

Article History

Received: January 26, 2024 Accepted: January 29, 2024 Published: January 31, 2024

Abstract

Mobile health (mHealth) applications have demonstrated immense potential for facilitating preventative care and disease management through intuitive platforms. However, realizing transformational health objectives relies on creating accessible tools optimized for different users. This research analyses mHealth app usability data sourced from online repositories to reveal the impact of usability (ease of use) from evaluating mobile health applications. Thoroughly examining interfaces with a utilization of statistical tests of significance, platform, integrations, and various application features shows complex relationships between usability and users experience. This work shows that applying random forest models can accurately classify the ease-of-use of mHealth applications. This work sheds light on the connections between design choices and their effects, guiding intentional improvements to expand the reach of mHealth. It does so by providing insights into the subtle ways that people interact with mHealth applications. The methodologies and findings provide actionable insights for developers and practitioners passionate about advancing digital healthcare.

Keywords: MHealth Applications; Usability; Artificial Intelligence; Data Science; Artificial Neural Network; Chi-Square; Random Forest; Evaluation Metrics; Random Oversampling; Feature Engineering; Feature Selection; Cross Validation; Research Hypothesis; P-Value

Abbreviations: ANN; WHO; PACMAD; iOS; SMOTE; EDA

Introduction and Background

The easy accessibility to mobile phones has revolutionized the way people monitor their health by giving access to healthcare information and services at their fingerprints [1]. Mobile health is a medical practice using smartphones, sensors, personal digital assistants, wireless monitoring devices and the likes according to [2]. The utilization of mHealth applications have helped to reduce waiting times for appointments, the need for physical appointments and encourage self-care practices [1]. Despite the benefits of these applications, a study by Zhou et al. [3] revealed that nearly half of smartphone users stop using mHealth applications due to factors like hidden costs, sub-optimal user experience, loss of interest, and concerns about security.

Despite the numerous importance of mobile health applications, the applications are far from being perfect and people still finds them difficult to use. This cannot be overlooked due to the growth of the mHealth applications, which has made the need to improve the usability of mHealth applications essential. [4] stated that if a mHealth application is difficult to navigate or understand, patients may fail to fully benefit from it. Evaluating the usability of mHealth applications is therefore important to ensure they are meeting users' needs and supporting improved health outcomes [5]. This study assessed the impact of usability by evaluating mobile health applications. Usability testing provides insights into how real users interact with an interface and where they encounter problems or confusion [6]. This information can then guide development of a more intuitive, user-friendly design [7].

Background

Mobile health applications, also known as mHealth applications, are digital instruments that have opened a personalized wellness management system for individuals. These applications aim to engage users in managing their health and wellbeing through functions like appointment reminders, symptoms trackers, wellness managers and patient portals. However, the usability of mHealth applications varies, and poor usability threatens their effectiveness and adoption (Kasali et al., 2019).

The easy availability of mHealth applications have open new ways of accessing healthcare and personalized wellness management system. This has empowered users with the tool to take proactive control of their health. However, these applications can only function well if they are designed with focus on usability (ease of use) and overall user experience. Many researchers have explored various aspect of mHealth applications usability but there are still gaps in understanding its full impact on user experience. Some papers solely focused on specific usability factors while others limited their approach to demographics influences on usability. This section examines previous studies on impact of the usability by evaluating mHealth applications. Additionally, we will compare our own objectives with the examined previous studies with the goal of contributing to the advancement of mHealth applications.

In 2018, [8] focused on the absence of efficient models for evaluating mHealth applications. The paper employed a hybrid evaluation approach for mHealth education applications, based on selected metrics from heuristic evaluation and usability evaluation. A guidance tool for evaluating mHealth education applications for improving the applications' usability and usefulness was proposed [9].

[10] primarily concentrated on mHealth applications designed for Type 2 Diabetes Mellitus (T2DM) patients. They employed three different multi-criteria decision-making (MCDM) methods to assess the usability of five specific mHealth applications. This study intends to broaden its focus beyond mHealth applications exclusively tailored for T2DM patients, examining many mHealth applications which is the notable limitation of this work. Consequently, the study may not comprehensively address the distinct usability requirements and challenges associated with mHealth applications designed for different health conditions or diverse user populations.

[11] investigated the usability of mobile health apps in Bangladesh with a 3-stage approach of keyword searches, heuristic evaluations of randomly selected apps and System Usability Scale (SUS). Results show over 60% of major heuristic violations, especially in aesthetic design indicating concerning usability in Bangladesh that may hinder adoption. A human-centered design approach is necessary for improvement and wider mobile health service uptake. A significant constraint of this project is that it exclusively centered on mobile health applications within Bangladesh, making it challenging to infer the findings to different countries.

(Kasali et al., 2019) developed a model for evaluating mHealth apps, implementing 23 usability features based on the Integrated Measurement Model and PACMAD model. The study tested the model with Google-Fit and MyfitnessPal, highlighting its potential for guiding developers in making effective decisions. However, our goal is to enhance this approach by addressing the study's limitations by considering both iOS and Android operating systems.

Objectives

The objectives of the study are listed as follows:

- Evaluate usability through features like ease of use, complexity, platforms, learnability, operating system, difficulty, and interaction flow.
- Develop usability guidelines for developers; measure how usability affects user satisfaction and engagement.
- Create a predictive model using machine learning to classify usability.

Overall, the goal is to thoroughly examine mHealth app usability and its real-world impacts essentially.

Research Questions

Mobile health (mHealth) applications offer immense potential to engage users in managing their health and wellbeing. However, the level of usability in mHealth app design varies and poor usability undermines their effectiveness. This poses important research questions around optimal methods for evaluating mHealth app usability and its impact on the user experience. Specifically, this project will look at the following:

i. What are the primary usability attributes that significantly influence users of mHealth applications?

ii. To what extent does the usability of mHealth applications influence frequent usage and loyalty to the platform?

iii. What demographic characteristics are associated with the primary users of mobile health apps, and how do these users perceive the ease of use of the applications?

iv. Do mHealth app users exhibit a preference for a specific operating system (iOS, Android, or both), and how does this preference impact their overall satisfaction with the application?

Research Hypothesis

A well-defined hypothesis sets a clear path for research, outlining the goals and objectives of an investigation. Clear research hypotheses pose specific, measurable questions that guide studies. These hypotheses determine the key study elements, such as variables, metrics, and data, for thorough comparisons of mobile health applications [12].

- H0 (Null Hypothesis): Usability (ease_of_use) HAS NO Impact in the Evaluation of mHealth Apps.
- H1 (Alternative Hypothesis): Usability (ease_of_use) HAS AN Impact in the Evaluation of mHealth Apps.

In this study, hypothesis testing reveals usability has significant impacts on mHealth apps with p-values below 0.05 for features like learnability, complexity, authentication, integration, and technical support, as shown in Figure 1. This supports not rejecting the alternative hypothesis.

Materials and Methods

Dataset Description

The dataset was sourced from an online repository, specifically selected due to its rich of features suitable for the comprehensive analysis of this project. Its wide variety of attributes makes it incredibly useful for conducting a detailed and comprehensive analysis. This dataset includes applications that cover a range of purposes, like monitoring of blood sugar levels, managing blood pressure, coping with depression, handling weight issues, and more. 2000 individuals took part in the survey, sharing insights that generated this data which consists of different types of information including binary and ordinal categorical, and numerical values, with 51 features in the dataset.

Data Cleaning and Pre-Processing

Real-world raw data often suffers quality issues like missing values and anomalies that impact analysis [13]. Data pre-processing detects and rectifies errors, removes outliers, and addresses missing data through imputation for enhanced accuracy in quantification [14].

The dataset contained features with complex names which were rename appropriately for better understanding. Some of the features considered irrelevant to the aim of this project were dropped using domain knowledge. Wrong and duplicated entries were detected and treated appropriately.

Handling Missing Values in the Target Variable: Missing values were found in the label and their imputation can introduce bias. The integrity of the obtained sample should be maintained to be a true representation of the population, and the values in the target class are to be in their truest form. Imputing the target variable might make the model appear more accurate than it is, which can be misleading and may lead to incorrect conclusion about the model's performance. Missing values can be handled by deleting affected rows [15]. The missing rows in the target variable were dropped because it is impossible to train the model effectively with null values especially when implementing supervised learning algorithm.

Handling Missing Values in Other Features: Various methods can be used to mitigate the influence of missing data on the overall findings and interpretations such as filling the null values with measures of central tendency which is a simple imputation procedure suitable for filling categorical features [16]. Hence, the features were filled with necessary with mode since it works best with categorical variables.

Feature Engineering

Identifying and transforming the best features that would aid data modelling and analysis. Features like platforms and targeted audience with plenty categories were transformed to reduce data redundancy. The main feature that describes usability 'ease of use' was grouped into Not Easy to Use, Neutral, Easy to Use and Very Easy to Use. The engineered features create a numerical feature representation suitable for modelling [17] which helps in ensuring accurate prediction and detailed analysis of mHealth applications.

Feature Selection

Selecting features entails picking out a precise set of relevant attributes from datasets to build models. This pivotal step in machine learning aims to boost model performance, simplify model complexity, and reduce the risk of overfitting [18]. Filter-based methods directly employ preselected learning algorithms to assess the features which was backed the work of (Lenz, 2016) that discussed the assumptions, interpretations, and applications of the chi-square test, making it an essential resource for understanding statistically significant dependencies among categorical features. Therefore, since our features are categorical after cleaning and dropping irrelevant variables, the chi-square method was employed to identify significant features in constructing the model, as illustrated in the Figure 1. Features with p-values less than level of significance (0.05) are statistically significant and selected for modelling Figure 2.

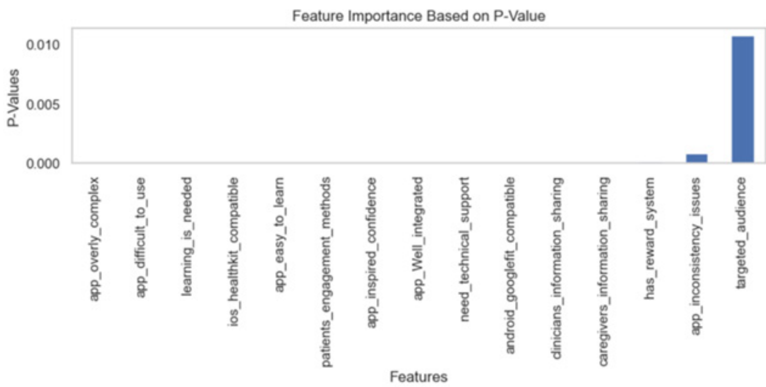

Figure1: Feature Importance with P-Values from Chi-Square Test of Significance.

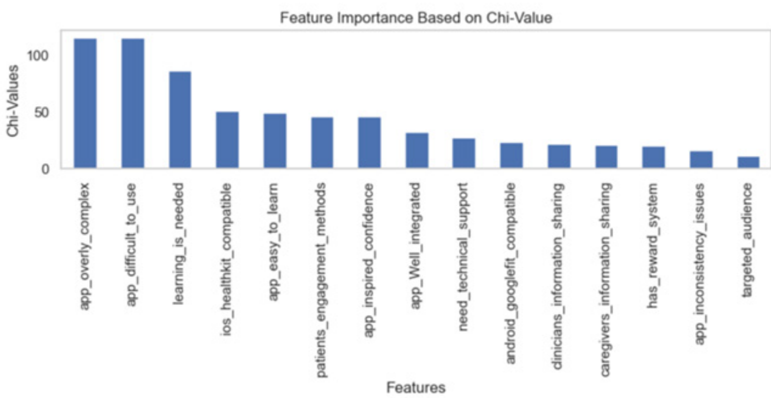

Figure 2: Feature Importance with Chi-Values from Chi-Square Test of Significance.

Exploratory Data Analysis

Exploratory data analysis (EDA) is a method used by data scientists to investigate datasets, spotting patterns, anomalies, and connections before diving into formal statistics or modeling. It's like a detective work that helps us find good ideas to test and make sure our predictive models are accurate. Key exploratory data analysis (EDA) methods include computing statistics, creating visual aids like scatter plots, histograms, and heat maps, and organizing data to make it easier to understand (Tukey, 1977). To assess ease-of-use, we'll calculate the ease of use across all refined features of the mobile health app to uncover their usual performance patterns.

Analysis

The ease of use of mobile health applications plays a pivotal role in shaping users' behaviours driving consistent engagement and fostering positive health outcomes. In exploring the relationship between ease of use and user engagement in mobile health applications led to looking at usability and the psychology behind user behaviour on how they use the applications. The graph below shows relationship between ease-of-use and app frequency [Figure 3].

Users who perceive the application as very easy to use are more likely to engage with it more frequently while users that did not find the application easy to use tend to use the application less. This observation aligns with established user behavior theories, emphasizing the influential role of usability in encouraging sustained user engagement. Understanding this pivotal role of ease of use in user behaviour offers critical insights for app designers and developers. Putting emphasis on intuitive interfaces, effortless navigation, and user-friendly features can greatly influence how much users engage with mobile health applications and how likely they are to keep using it.

The extent to which the usability of a mHealth application could be influenced by screen size of the devices of the use can be explored by checking the relationship between platform and ease of use. The Table 1 below shows that 92% of users that found the applications Very Easy to Use are tablet users. It is depicted in Figure 4 above that ease of use is at its peak in the region where the value of the platform is equivalent to Tablet, which shows that users found apps built for tablets (Very Easy to Use) compared to other. Screen sizes might come from several factors such as optimized layout, responsive design, visual appeal and many more, influencing their choice.

Various users utilize mHealth applications to manage health issues such as dementia, pain, stroke, coronary artery problems and the likes. Among those who found the app very easy to use approximately 24% are using it to address serious health concerns. Figure 5 illustrates the diverse user responses based on the application's ease of use.

The plot shows that 15% of the brain related users rated the applications NOT_EASY_TO_USE in comparison to other user groups. Users with conditions like dementia might struggle with remembering login credentials, navigation steps, or using complex features within the app. Some users may find it challenging to process complex views, leading to confusion or difficulty following sequential steps in the app [Figure 6].

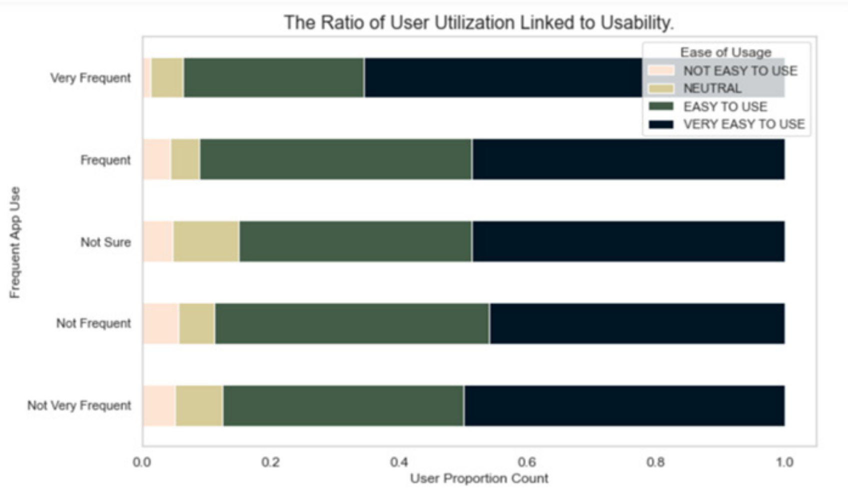

Figure 3: Relationship Between Usability and Frequent Usage.

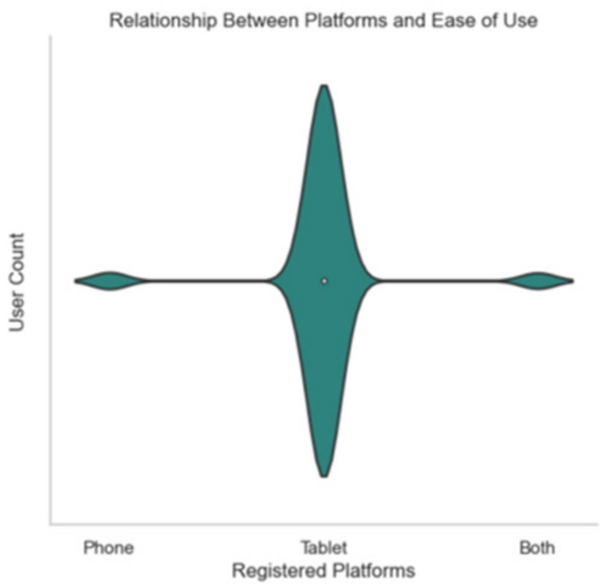

Figure 4: Relationship Between Usability and Platform.

Citation: Kayode OJ, Jaber TA, Gordon N. Application of Artificial Intelligence and Data Science in Detecting the Impact of Usability from Evaluation of Mobile Health Applications. *Int J Eng Tech & Inf.* 2024;5(1):1-9. DOI: 10.51626/ijeti.2024.05.00070

Table 1: Users' Platform Distribution.

Platform	Users' proportion (%)
Phone	3.93
Tablet	92.36
Both	3.72

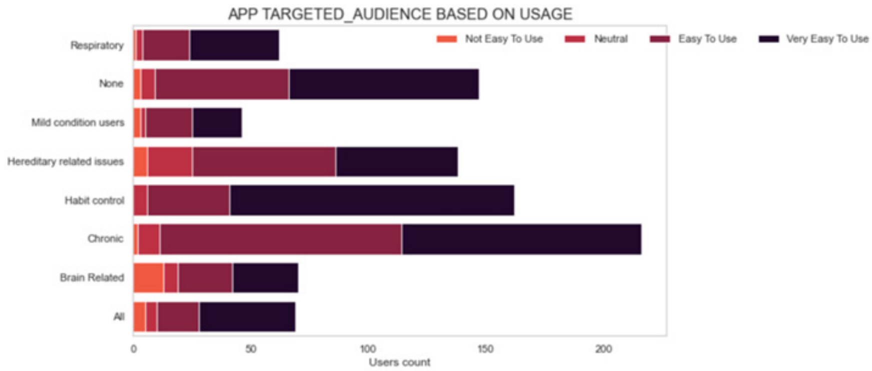

Figure 5: Relationship between Usability and Target Audience.

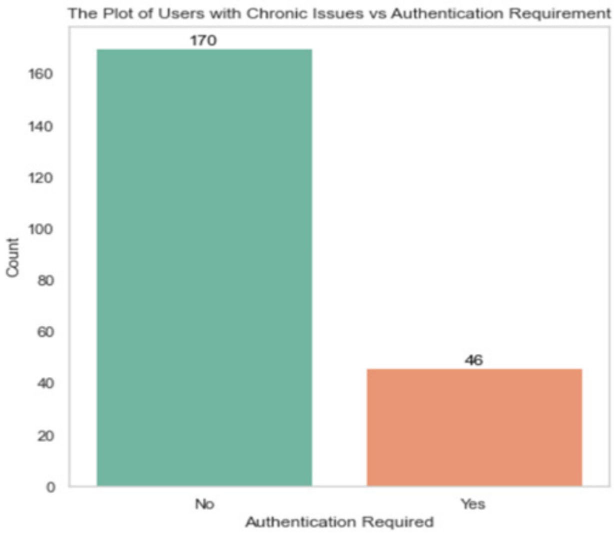

Figure 6: Relationship Between Chronic Users with Login Requirement.

Further investigation into 'has authentication' feature revealed that 70% of users consider that the application is Very Easy to Use when the applications do not require them to login. Hence, within the brain related users, it was noted that most of the applications that target the users require them to access the application with sort of credentials. This emphasizes that the presence of login requirement among brain related users contributed to their proportion of "not_easy_to_use" experience when compared to other users.

The plot shown in Figure 7 describes the relationship of operating system with respect to the ease of use of the mHealth application. It indicates that users find the applications very easy to use regardless of the operating system used to develop them. This similarity is evident in the ratio of users who find the app very easy to use, whether on iOS, Android, or both. However, there's a slightly higher proportion of users expressing dissatisfaction with usability among those utilizing Android. The proportion adoption of the feature can be seen in Figure 8.

Classification Model

The feature selection process involved employing the chi-square method suitable for categorical data, revealing the top 15 features with p-values less than 0.05 (level of significance) in constructing the predictive models. Categorical features within the dataset were converted into numerical values through label encoding. Class distribution in the dataset was found to be imbalanced which was solved using the SMOTE library to introduce minority class values, thereby creating a more balanced distribution. Following this, the dataset was divided into training and test sets using 80/20 split meaning 80% of the data was used to train and the reaming to test. To enhance algorithm performance, the data underwent scaling method and helps optimize the algorithms' performance. Lastly, four predictive models were aimed at predicting the usability of mHealth applications. The predictive outcomes were categorized into 'Not Easy to Use', 'Neutral', 'Easy to Use' and 'Very Easy to Use' groups.

Model Selection

Choosing the right predictive modeling methods is crucial for accurately evaluating the usability of mHealth apps, considering how they're used. This section explores factors to consider when selecting models for usability classification. Complex nonlinear models such as neural networks can capture difficult usage patterns, while simpler models offer easier interpretation for actionable insights [19]. Hence, both would be considered in this work. Carefully choosing predictive models to quantify app usability ensures adaptability, accessibility of insights for developers, and the ability to accommodate changes over time, which is crucial for long-term value. The first classifier, KNeighbours Classifier, predicts based on the majority class among its nearest neighbors. The second is the random forest classifier, an ensemble method that avoids overfitting by combining multiple decision trees. The third classifier is a Decision Tree, representing features and class labels in a tree-like structure. Lastly, logistic regression estimates the probability of an instance belonging to a specific class based on input features. Thereafter, Artificial Neural Network was utilized in rebuilding the model because they are employed to describe or to find linear relationship as well, but the result might often be worse than that if using another simpler standard statistical technique [20,21]. Its performance shall be discussed in the next section in comparison to the performances obtained from other models [22, 23].

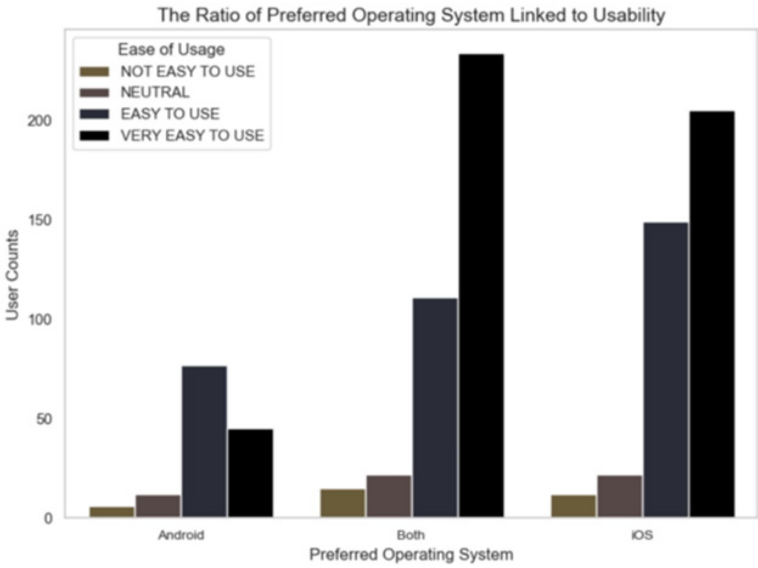

Figure 7: Relationship between Usability and Operating System.

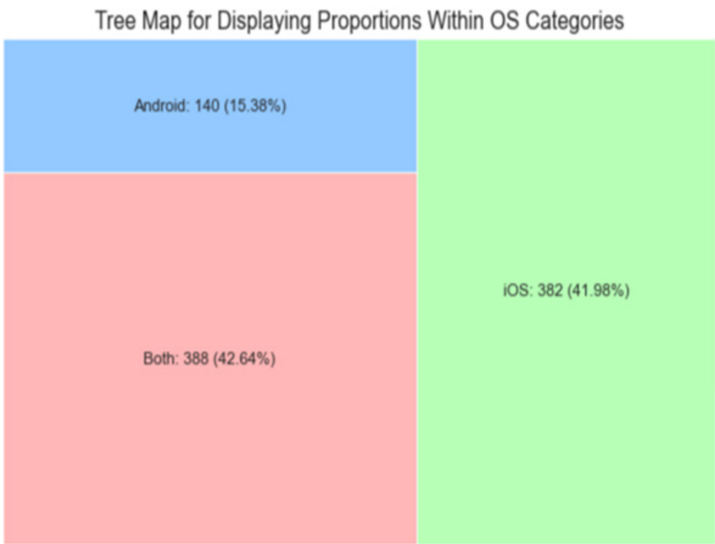

Figure 8: Tree Map of Proportions of Operating System Categories.

Result

The classification of the ease-of-use was built on four Machine Learning algorithms and one deep Learnings technique. Recall is chosen as the metrics of evaluation for these models because it is crucial to avoid false leads in medical related studies [Table 2, 3]. It measures the model's ability to correctly identify positive instances out of all actual positives. Higher recall signifies fewer false negatives, indicating that the model captures more of the actual positive instances. The Table 4 shows both the recall and precision values for the models adopted in the project. F1 score has also been selected as an evaluation metric because we used random oversampling to balance the dataset, and the Random Forest Classifier is the best performing classifier with a recall score of 0.93 [Table 5, 6].

Table 2: Classification Models Result on the Test Sets.

Model	Precision	Recall	F1-Score
KNeighbours Classifier	0.86	0.86	0.85
Random Forest	0.93	0.93	0.93
Decision Tree	0.86	0.86	0.86
Logistic Regression	0.62	0.62	0.62

Table 3: Random Forest Classifier Result on the Training Set.

	Precision	Recall	F1-Score
Not Easy to Use	1.00	0.99	0.99
Neutral	1.00	0.99	0.99
Easy To Use	0.95	0.96	0.96
Very Easy to Use	0.96	0.97	0.96
Accuracy	-	-	0.98
Macro avg	0.98	0.98	0.98
Weighted avg	0.98	0.98	0.98

Table 4: Random Forest Classifier Result on the Test/Validation Set.

	Precision	Recall	F1-Score
Not Easy to Use	0.99	0.97	0.98
Neutral	0.96	0.94	0.95
Easy to Use	0.87	0.91	0.89
Very Easy to Use	0.89	0.89	0.89
Accuracy	-	-	0.93
Macro avg	0.93	0.93	0.93
Weighted avg	0.93	0.93	0.93

Table 5: Artificial Neural Network Result Training Set.

	Precision	Recall	F1-Score
Not Easy to Use	0.93	0.94	0.93
Neutral	0.81	0.96	0.87
Easy to Use	0.83	0.69	0.75
Very Easy to Use	0.91	0.86	0.88
Accuracy	-	-	0.86
Macro avg	0.86	0.86	0.86
Weighted avg	0.86	0.86	0.86

Table 6: Artificial Neural Network Result on the Test/Validation Set.

	Precision	Recall	F1-Score
Not Easy to Use	0.87	0.91	0.89
Neutral	0.66	0.94	0.77
Easy to Use	0.67	0.48	0.56
Very Easy to Use	0.91	0.76	0.83
Accuracy	-	-	0.77
Macro avg	0.78	0.77	0.76
Weighted avg	0.78	0.77	0.76

The model performed well on the test set by accurately classifying usability of mHealth apps with a recall of 93%. Cross validation method was implemented with (3, 5, 10, 15 folds) and an average score of 0.7890 with a standard deviation of 0.0150 at cv=5 was obtained on Random Forest. This suggests the model should work well with new data, not just the samples it was trained on. The result obtained from ANN model showed 0.77 recall score on Test Set. The table shows that Random Forest model outperform ANN which may be due to ANN requiring large amount of data to perform well. For a small dataset with simple relationships like ours, a simpler model like a Random Forest may be sufficient.

Discussion

In this study, the datasets were analyzed based on four research questions:

What demographic characteristics are associated with the primary users of mobile health apps, and how do these users perceive the ease of use of the applications?

The primary users found in the dataset are people with various health issues ranging from brain related, hereditary, chronic patients and the likes. Analysis indicates mHealth apps overall hold positive usability perceptions, though some variability exists across user segments. Most found the applications very easy to use, but some of the brain related users struggled more with login requirement, subsequently affect their ability to use the application easily. Additionally, those facing serious conditions like chronic illnesses considered apps highly usable given little to no authentication process requirement within the application as illustrated in Figure 5. This analysis showed that different users have unique reaction to ease of use of mHealth applications which helps to improve on the work of [10].

Do mobile health app users exhibit a preference for a specific operating system (iOS, Android, or both), and how does this preference impact their overall satisfaction with the application?

Yes, it was observed that users found the mHealth applications built with iOS operating system easier to use when compared with android. This could be as a result that iOS applications adhere to a lot of human interface guidelines, ensuring a consistent and familiar user interface across applications. It is also good to note that iOS applications often prioritize simplicity and straightforward navigation, allowing users to intuitively interact with the interface, thereby enhancing ease of use. This work helps to justify the claim of analyzing usability on different operating systems rather than focusing on just one because it showed how operating system affect ease of use hence addressed the limitation of (Kasali et al., 2019).

Which model performs best in classifying the ease of use of mHealth applications?

Amongst all the models used to predict how easy mHealth apps are to use, the Random Forest Classifier came best. It scored 0.93 on the weighted recall on the test set, performing better than the remaining models.

To what extent does the usability of mobile health applications influence frequent usage and loyalty to the platform?

Ease of use plays a significant role in how well users tend to use the application. It was observed that mHealth applications developed to be easy to use by users encourage them to continue to use the application and subsequently affect their usage patterns in a positive manner [3] had earlier reported that users discontinue using application majorly because of suboptimal user experience which comprised of usability issues such as design flaws, functionalities issues, navigation problem, inconsistency and many more. The analysis done in this work has been able to show that if mHealth applications are easy to use, users will reward them with their loyalties.

Future Work

These findings highlight promising pathways for strengthening mHealth applications design. However, fully realizing this potential requires extending evaluations across more different applications. Future work calls for extending evaluations across wider application varieties. Specifically, incorporating emerging technologies like virtual reality, chatbots and plugins can enhance inclusiveness. The goal lies in using these learnings into broadly applicable specifications and guiding developers with best practices for maximized accessibility. Overall, this research provides a meaningful progress for advancing rigorous inclusive design principles.

Conclusion

This paper offers important findings about how app features affect how easy it is to use mHealth apps and the models used to predict this. The research discovered that users dealing with serious illnesses found the apps the easiest to use. It also revealed that apps needing extensive logins and having integration issues had lower usability ratings. The key takeaway is that when developing mHealth apps, considering their usability should be prioritized. Making them easy to use could be a game-changer, helping these apps have a bigger impact on users' adoption of the apps, continuous usage, and health outcomes for everyone.

References

1. Rathbone AL, Prescott J (2017) The use of mobile apps and SMS messaging as physical and mental health interventions: systematic review. J Med Internet Res 19(8).
2. (2011) WHO Global Observatory for eHealth MHealth: new horizons for health through mobile technologies: second global survey on eHealth. World Health Organization.
3. Zhou L, Bao J, Watzlaf V, Parmanto B (2019) Barriers to and Facilitators of the Use of Mobile Health Apps from a Security Perspective: Mixed-Methods Study. JMIR MHealth and UHealth 7(4): e11223.
4. Kumar S, Nilsen WJ, Abernethy A, Atienza A, Patrick K, et al. (2013) Mobile health technology evaluation: the mHealth evidence workshop. American journal of preventive medicine 45(2): 228-236.
5. Zapata BC, Fernández Alemán JL, Idri A, Toval A (2015) Empirical studies on usability of mHealth apps: a systematic literature review. J Med Syst 39(2): 1.
6. Bargas Avila JA, Brenzikofer O, Roth SP, Tuch AN, Orsini S, et al. (2010) Simple but crucial user interfaces in the world wide web: introducing 20 guidelines for usable web form design. User Interfaces 1(1): 26-46.
7. Schnall R, Iribarren SJ (2015) Review and analysis of existing mobile phone applications for health care-associated infection prevention. American journal of infection control 43(6): 572-576.
8. Aljaber Tareq, Gordon Neil (2018) A Hybrid Evaluation Approach and Guidance for mHealth Education Applications.
9. Aljaber T, Gordon N (2017) A guidance and evaluation approach for mHealth education applications. 330-340.
10. Gupta K, Roy S, Poonia RC, Nayak SR, Kumar R, et al. (2021) Evaluating the Usability of mHealth Applications on Type 2 Diabetes Mellitus Using Various MCDM Methods. Healthcare 10(1): 4.
11. Islam MN, Karim Md M, Inan TT, Islam AKMN (2020) Investigating usability of mobile health applications in Bangladesh. BMC Medical Informatics and Decision Making 20(1).
12. Harrison R, Flood D, Duce D (2013) Usability of mobile applications: literature review and rationale for a new usability model. Journal of Interaction Science 1(1).
13. Van den Broeck J, Cunningham SA, Eeckels R, Herbst K (2005) Data cleaning: detecting, diagnosing, and editing data abnormalities. PLoS medicine 2(10): e267.

14. Hellerstein JM (2008) Quantitative data cleaning for large databases. United Nations Economic Commission for Europe (UNECE).

15. Ludbrook J (2008) Outlying observations and missing values: how should they be handled?. Clin Exp Pharmacol Physiol 35(5-6): 670-678.

16. Brownlee J (2020) Statistical Imputation for Missing Values in Machine Learning Machine Learning Mastery.

17. Zheng A, Casari A, Wang F (2018) Feature engineering for machine learning: principles and techniques for data scientists. O Reilly Media Inc.

18. Guyon I, Elisseeff A (2003) An introduction to variable and feature selection. Journal of machine learning research 1157-1182.

19. Wang Y, Wu T, Chen Z (2021) Active Usage of Mobile Health Applications: Cross-sectional Study. Journal of Medical Internet Research 23(12).

20. Zupan J (nd) Introduction to Artificial Neural Network (ANN) Methods: What They Are and How to Use Them. Acta Chimica Slovenica.

21. (2011) mHealth: New Horizons for Health Through Mobile Technologies: Second Global Survey on eHealth. World Health Organization.

22. Alan Agresti (2013) Categorical data analysis. Statistical Papers 57(3): 849-850.

23. Haldun Akoglu (2018) User's guide to correlation coefficients. Turk J Emerg Med 91-93.

Citation: Kayode OJ, Jaber TA, Gordon N. Application of Artificial Intelligence and Data Science in Detecting the Impact of Usability from Evaluation of Mobile Health Applications. *Int J Eng Tech & Inf*. 2024;5(1):1-9. DOI: 10.51626/ijeti.2024.05.00070