Machine Learning Model for Prediction of Smartphone Addiction

S Likhith
UG Scholor, dept. of Information Technology
Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College)
A.Rangampet, Tirupati,India
likhithsarvisetti@gmail.com

Chengamma Chitteti
Assistant professor, dept. of Data Science
Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College)
A.Rangampet, Tirupati,India
sailusrav@gmail.com

Dr. M Dharani
Assistant professor, dept. of ECE
*Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College)*A.Rangampet, Tirupati,India
dharani405@gmail.com

V Nivedhitha
UG Scholor, dept. of Information Technology
Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College)
A.Rangampet, Tirupati,India
nivedhithavalmiki@gmail.com

N Guna Geethika
UG Scholor, dept. of Information Technology
*Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College)*A.Rangampet, Tirupati,India
geethikac574@gmail.com

V Godwin
UG Scholor, dept. of Information Technology
Mohan Babu University(Erstwhile Sree Vidyanikethan Engineering College)
A.Rangampet, Tirupati,India
godwinv7849@gmail.com

***Abstract*—Smartphone addiction has become a growing concern in recent years, with increasing numbers of people exhibiting symptoms such as excessive phone use, loss of productivity, and even physical and psychological health problems. As a result, there is a need to develop effective tools for predicting smartphone addiction and identifying those at risk. In this study, we built a ML model used for predicting smartphone addiction using data collected from a survey of smartphone users. Demographics, phone usage habits, and a range of psychological issues like stress, anxiety, and depression were all covered in the poll. A popular and effective machine learning method, to build our model. In this study, the data is preprocessed by encoding categorical variables and normalizing numerical variables to ensure that the model could learn effectively. Further, the model is trained on some percentage of the data and evaluated its accuracy and its performance on the remaining percentage of the data using several metrics such as accuracy. The results showed that the model has achieved a high accuracy in predicting smartphone addiction. The most important features for predicting addiction were mobile phone usage patterns such as the frequency of checking notifications, the number of hours spent on the phone each day, and the types of apps used most frequently. Other important factors included age, gender, and stress levels. The model developed has several potential applications. It could be used by healthcare professionals to identify individuals who are at risk of developing smartphone addiction and provide appropriate interventions. It could also be used by app developers to design apps those are less addictive and promote healthier phone usage habits. In a brief, this study illustrates both the practicality and efficacy of using machine learning models for predicting smartphone addiction. Further research is needed to validate our findings on larger and more diverse datasets and to explore the potential applications of this model in different contexts.**

Keywords—Decision tree, Random Forest, Logistic Regression, Convolutional Neural Network (CNN) and Machine learning techniques.

I. INTRODUCTION

Over the past years, there has been a continuous growth in the usage of smartphones, which have become an essential part of our lives. Even while mobile phones have many advantages, using them excessively can cause addiction and have a detrimental effect on a person's productivity, social connections, physical and mental health, and relationships.

Models that predict smartphone addiction based on a variety of parameters, including social media usage, usage patterns of smartphones, demographic data, and psychological aspects, may be created using machine learning. These models can be used to detect people who may become addicted to smartphones and to help them receive the right assistance and therapies. Usually, the first step in creating a machine learning model to forecast smartphone addiction is gathering data from a sizable sample of people. Information on their social media and smartphone usage habits, as well as demographic details like age and gender and psychological characteristics like stress, anxiety, and depression, would all be included in this data. After the data is gathered, it is cleaned and preprocessed to eliminate any unnecessary or missing data points.

During the preprocessing of the data, it is required to replace imputations and label encoding. Replacing imputations means it can handle all the null values and replace them as 0 or 1 by considering the particular value as an outlier. Label Encoding modifies the categorical data into numerical values. Then the data will be preprocessed and it will be split into training data and testing data.

Next, based on the type of data and the problem at hand, an appropriate machine learning method is chosen. After that, the data is divided into two sets: a testing set and a training set. By providing the machine learning model with input characteristics and matching output labels, the training set is utilized to train the model. By identifying patterns in the data, the model is able to determine a correlation between the input characteristics and the output labels. The model is

2024 International Conference on Expert Clouds and Applications (ICOECA) | 979-8-3503-8579-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICOECA62351.2024.00163

tested on the testing set once it has been trained in order to assess its performance.

Accuracy is one of the measures used to gauge the model's performance. Until the model performs well enough, it is further improved by adjusting its parameters or using other methods. Once the model is created, user input features may be fed into it to forecast a person's likelihood of developing a smartphone addiction. A probability score showing the chance of developing a smartphone addiction is produced by the model. People who are at risk of addiction can receive the proper interventions and assistance based on their score. To sum up, machine learning models can be a useful tool for identifying those who are at risk of smartphone addiction and forecasting the likelihood of addiction.

These models can assist people in preventing addiction and lessening its harmful impacts, as well as healthcare professionals. Nonetheless, gathering high-quality data and creating precise, trustworthy models that work well in practical situations are crucial.

II. LITERATURE SURVEY

A quick synopsis of all the research conducted up to this point is provided in this chapter. Additionally, it summarizes all of the research studies that have been done up to this point on the prediction of smartphone addiction, including advancements in prior technology as well as the challenges that users face. As a result, this develops the project's problem statement, which explains bot development and performance challenges and suggests a recommended architecture to address them.

In a study by Demir and Akpinat (2018), the impact of mobile learning applications on students' academic performance and their perception of mobile learning was investigated.

This study looks at how undergraduate students' academic performance, attitudes toward mobile learning, and animation development levels are affected by mobile learning applications. The study's design was quasi-experimental. Students from Dokuz Eylul University in Turkey's Buca Faculty of Education participated in the study. The 2013–2014 school year's first semester saw the execution of the experiment. The experimental group (n = 15) employed a mobile learning technique, whereas the control group (n = 26) attended a lecture-based classroom. Students' attitudes toward mobile learning were gauged using an attitude scale, and the impact of mobile learning applications on students' academic performance was investigated using an achievement test. A criteria was utilized to assess the animations that the students had created. The students thought that mobile learning was a useful tactic that may significantly increase their motivation. It is imperative that scholars and professionals acknowledge that mobile learning has the potential to enhance students' motivation and positively impact their academic performance and achievements.

In a randomized controlled trial, Abadiyan et al. (2021) investigated the effectiveness of combining a smartphone application with global postural re-education to improve outcomes for people with nonspecific neck pain, including posture improvement, improved quality of life, and endurance.

This study examined the effects of integrating a smartphone app into an 8-week global postural reeducation (GPR) program on neck pain, endurance, quality of life, and forward head posture (FHP) in people with chronic neck pain and FHP. Thirty office workers with persistent neck pain (38.5 ± 9.1 years), twenty of whom were male and twenty of whom were female, were randomly assigned to one of three groups: group 1 (GPR with a smartphone app, n = 20); group 2 (GPR alone, n = 20); and group 3 (the control group, n = 20). The primary outcome was pain, followed by disability, quality of life, posture, and endurance in second and third place. Pain, disability, endurance, quality of life, and posture were measured pre- and post-8-week interventions using the visual analog scale (VAS), neck disability index (NDI), progressive iso-inertial lifting evaluation (PILE) test, quality of life questionnaire (SF-36), and photogrammetry, respectively. The data have been statistically examined using a one-way analysis of covariance (ANCOVA).

In an observational research , Osailan(2021) investigated the relationship between young people's hand-grip and pinch-grip strength and the amount of time they spent using their smartphones, as tracked by the device's screen time function.

Smartphone use has grown significantly, particularly among youth, for a variety of uses outside of communication, such as online gaming and surfing. One of the primary issues linked to the growing usage of cellphones is wrist and hand weakness. Flexion and extension of the wrist, thumb, and fingers causes this weakening and serious musculoskeletal disease. The association between hand and pinch grip strength and the length of time spent using a smartphone to track screen time is not well understood. Thus, the aim of the research was to look into the relationship between young people's hand and their pinch grip strengths and the length of time they spend using smart phones. One hundred teenage boys offered their time to take part in the research. A digital scale and a portable stadiometer were used to quickly measure each participant's height and weight. A handheld dynamometer was used to assess the strength of the hand and pinch grips. The amount of time spent on smartphones was calculated using the average daily screen time over the previous seven days.

III. PROPOSED MODEL

By utilizing machine learning to forecast addiction tendencies in smartphone users, the suggested approach tackles the growing problem of smartphone addiction. It uses a multipronged strategy, combining classification methods to examine various datasets that include psychological variables like stress, anxiety, and depression as well as demographic data and phone usage patterns. By means of extensive survey data collecting, the system obtains relevant information necessary for predictive analysis. After that, a thorough preprocessing step is carried out to tidy and prepare the gathered data so that machine learning algorithms may work with it. The purpose of this preprocessing step is to optimize the quality of the data for the next model training stage by encoding categorical variables and addressing missing values.

The core of the suggested approach is its model training stage, which trains machine learning algorithms to anticipate smartphone addiction tendencies using preprocessed data. By utilizing the Python programming language and well-known machine learning libraries like TensorFlow and scikit-learn, the system creates reliable predictive models that can identify patterns suggestive of addiction risk. These models have the capacity to effectively handle massive amounts of data, allowing for prompt forecasts and responses. Additionally, optimization strategies like parallel processing and model caching support the system's scalability and speed, guaranteeing quick and precise forecasts even with rising user demands.

The suggested system's easy integration and interoperability with current survey platforms and mobile applications streamlines the data collection procedures.

There are numerous expected advantages to the suggested system. It enables stakeholders to intervene proactively and offer tailored support by facilitating the early identification of tendencies towards smartphone addiction among users. Additionally, the approach improves knowledge of the intricate interactions between variables that lead to addiction, which makes it easier to create individualized therapies and preventative measures. The ultimate goal of the suggested approach is to encourage better smartphone usage practices and enhance users' general wellbeing in the current digital era.

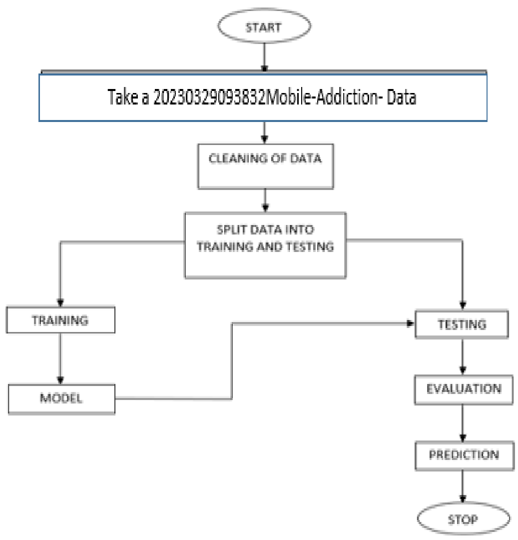

Fig 1. Block Diagram of Proposed System

3.1. *Algorithms:*

The research has shown that these specified algorithms were more reliable and were more accurate for a problem requiring prediction or classification. Among the 5 algorithms considered, 3 of them were ML algorithms and others belong to Deep Learning. The deep learning algorithms were chosen to ensure novelty in the project by implementing something different than the previous studies. The Adam optimizer builds a sequential model and connects the input, output layers with different types of layers and build a strong network.

3.1.1. *Decision Tree:*

Regression and classification are only two of the many areas of machine learning that have been impacted by trees, as seen by the abundance of real-world parallels for trees. To officially and graphically represent decisions and decision-making, decision analysis can make use of decision trees. As the name implies, it uses a decision-tree model. Despite being a widely used data mining method for choosing a course of action to reach a certain goal.

An inverted decision tree graphic shows the root at the top. In the picture on the left, the bold black text indicates an internal node or condition, from which the tree branches out into edges. The decision or leaf in this case denotes the end of the branch that is no longer capable of splitting.

3.1.2. Random Forest:

One machine learning method for handling regression and classification issues is the random forest algorithm. It employs ensemble learning, a technique that combines a large number of classifiers to tackle complex problems. Multiple decision trees make up the random forest algorithm. The random forest method learns its "forest" by bagging or bootstrap aggregating. Machine learning algorithms get more precise thanks to an ensemble meta-algorithm known as bagging.

The (random forest) technique uses the predictions from the decision trees to decide the outcome. It generates predictions by averaging, or meaning, the output from several trees. The more trees used, the outcome will be more accurate.

3.1.3. Logistic Regression:

Logistic regression was used in the biological sciences in the early 1900s. It was then extensively used in social science domains. Logistic regression is used when the dependent variable (target) is categorical. For example, To ascertain if an email is spam (1) or (0) The malignancy (1) or absence of the tumor (0)

Consider a scenario where we have to decide if an email is spam or not. To solve this problem with linear regression, we first need to define a threshold that dictates which classifications may be finished. If the projected continuous value is 0.4, the threshold value is 0.5, and the actual class is malignant, for instance, the data point will be classified as non-malignant.

3.1.4. Adaptive Moment Estimation (Adam):

Adam, or Adaptive Moment Estimation, is an optimization algorithm used to train deep neural networks. It combines concepts from RMSProp and Momentum to adaptively adjust learning rates for individual parameters. This adaptability improves convergence speed and performance, especially in scenarios with varying gradients.

Additionally, Adam incorporates momentum to maintain consistent directionality during optimization and includes bias correction mechanisms for more accurate parameter estimates. Overall, Adam is renowned for its effectiveness, efficiency, and widespread applicability in deep learning tasks.

3.1.5. Multi Layer Perception(MLP):

A Multi-Layer Perceptron (MLP) is a neural network architecture composed of interconnected nodes arranged in multiple layers. These layers include an input layer for receiving data, hidden layers for processing information, and an output layer for producing predictions or classifications. Through weighted connections between nodes, information is transmitted from one layer to the next.

Activation functions within the network introduce non-linearities, enabling the model to capture complex relationships in the data. MLPs find widespread use in tasks such as classification and regression due to their flexibility. However, they are prone to overfitting, where the model learns to memorize the training data instead of generalizing, and they can become computationally demanding when dealing with large datasets.

One of the five algorithms is selected to build the model using our training dataset. The accuracy of the model can be seen and the result will be shown after entering answers for the entire questionnaire.

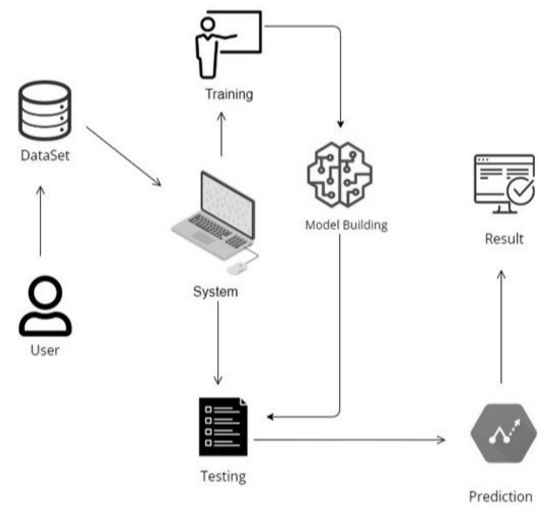

Fig 2. Architecture Diagram

IV. METHODOLOGY

The primary focus during project development has been performance. This project has been developed effectively using a variety of ways, enabling users to develop and host. This chapter provides a thorough internal grasp of the workflow and sequencing of the real project process by describing the numerous UML diagrams.

4.1. Use-case Diagram:

A use-case analysis in the Unified Modeling Language (UML) produces a use case diagram, which is a type of behavioral diagram. Its purpose is to give a visual representation of the functionality that a system delivers in terms of actors, use cases (which are representations of their objectives), and any relationships between those use cases. Showing which actors acquire which system features is the main purpose of a use case diagram.

The roles played by the actors in the system can be shown:

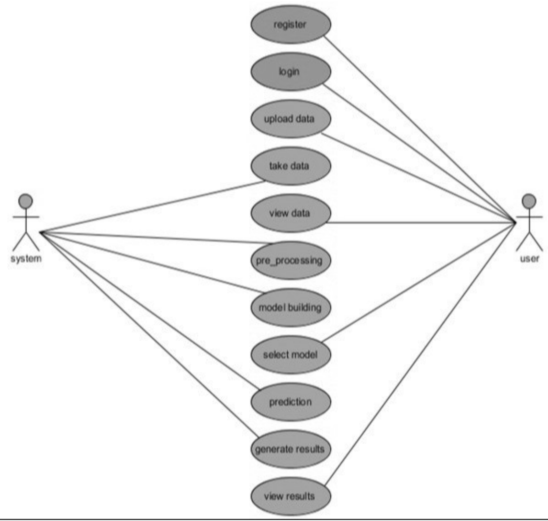

Fig 3: Use Case Diagram

4.2. Activity Diagram:

Using activity diagrams, workflows made up of consecutive actions and choices with concurrency, iteration, and representation are visually depicted. The step-by-step operational and business operations of system components may be explained using activity diagrams in the Unified Modeling Language. The overall control flow is depicted in an activity diagram.

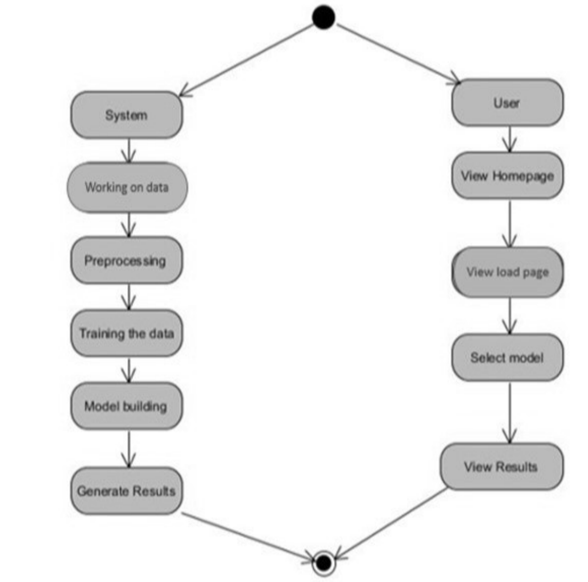

Fig 4: Activity Diagram

V. EXPERIMENTAL RESULTS

Results are obtained using the dataset that includes 21 characteristics and 500 tuples that cover a range of smartphone usage and addiction-related behaviors. Features include personal information such as the timestamp, complete name, and gender in addition to questions about social behavior, battery dependence, phone usage habits, and reliance on the device in different situations. Insights regarding user patterns may be gained from responses to queries like using the phone for academic purposes, buying books digitally, and anxiety linked to batteries.

Home Page: User can view the Home page

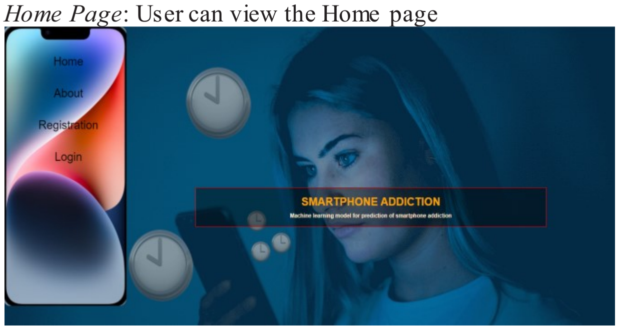

Fig 5: Home page

About: This page shows a small information about project

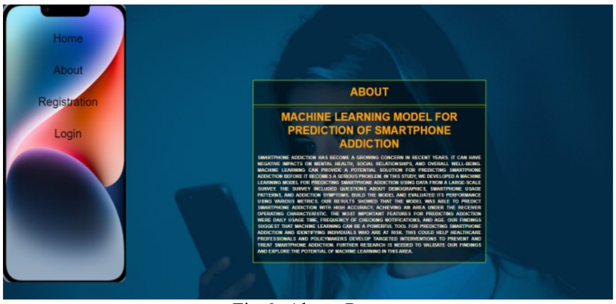

Fig 6: About Page

User Registration page: User can register with required details.

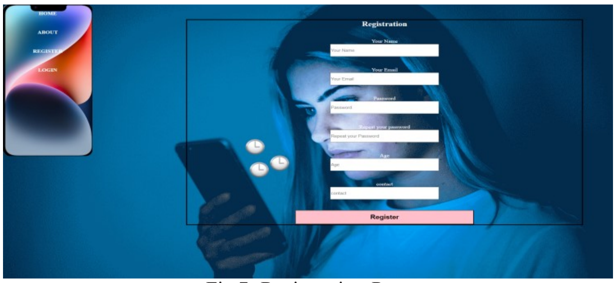

Fig 7: Registration Page

View Data: User can view the data

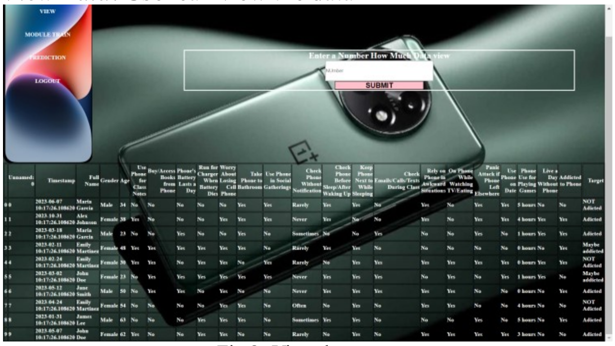

Fig 8: View data page

Model: Train the model

The algorithm can be selected in the drop-down and the accuracy will be displayed in the same page.

Fig 9: Model Page

Prediction: User can give a input and view The Prediction

After answering all the questions, we can view our final result which is "addicted" or "not addicted".

Fig 10: Prediction Page

VI. CONCLUSION

For this project, we used machine learning model approaches such decision trees, random forests, logistic regression, Multi-Layer-Perceptron (MLP) and Adam (Adaptive Moment Estimation) to create a user-friendly application named prediction of smartphone addiction. Using the finest methods we could find, we were able to demonstrate that while some people are not addicted, they may be. We have successfully developed a user-friendly application in this project that uses Machine Learning Model approaches to predict smartphone addiction. The goal was to provide a workable way to identify those who could be at risk of developing a smartphone addiction. For the most accurate forecasts, this study has carefully selected and adjusted these machine learning algorithms and developed a strong prediction model by utilizing a broad dataset that included several variables including screen time, app usage, and self-reported behaviors. This approach offers important insights into consumers' smartphone usage behaviors by classifying them into three groups: possibly addicted, not addicted, and addicted.

VII. REFERENCES

[1] Demir, K. & Akpinat, E. The effect of mobile learning applications on students' academic achievement and attitudes toward mobile learning. Malays. Online J. Educ. Technol. 6, 48–59 (2018).

[2] Abadiyan, F., Hadadnezhad, M., Khosrokiani, Z., Letafatkar, A. & Akhshik, H. A randomised controlled trial aimed at improving neck pain, posture, quality of life, and endurance in individuals with nonspecific neck pain by incorporating a smartphone app into global postural re-education.Trials 22, 274 (2021).

[3] Osorio-Molina, C. et al. A systematic review and meta-analysis of smartphone addiction among nursing students, risk variables, and its detrimental impacts. Nurse Educ. Today 98, 104741 (2021).R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[4] Osailan, A. B An observational study examined the association between young people's hand and pinch grip strength and the length of time they used their smartphones to track screen time. MC Musculoskelet. Disord. 22, 186 (2021). M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[5] Hitti, E., Hadid, D., Melki, J., Kaddoura, R. & Alameddine, M The prevalence, use, and attitudes of mobile device use among emergency department healthcare personnel.. Sci. Rep. 11, 1917 (2021).

[6] Shaygan, M. & Jaberi, A. The impact of a smartphone-based pain management software on teenagers with chronic pain's quality of life and level of discomfort. Sci. Rep. 11, 6588 (2021).

[7] Sohn, S. Y., Krasnoff, L., Rees, P., Kalk, N. J. & Carter, B. The association between smartphone addiction and sleep: A UK cross-sectional study of young adults. Front. Psych. 12, 629407 (2021).

[8] Wilkerson, G. B. et al. Wellness survey responses and smartphone app response efficiency: Associations with remote history of sport-related concussion. Percept. Mot. Skills 128, 714–730 (2021).

[9] Thornton, L. et al. A multiple health behavior change, self-monitoring mobile app for adolescents: Development and usability study of the Health4Life App. JMIR Format. Res. 5, e25513 (2021).

[10] Joo, E., Kononova, A., Kanthawala, S., Peng, W. & Cotten, S. Smartphone users' persuasion knowledge in the context of consumer mHealth apps: Qualitative study. JMIR Mhealth Uhealth 9, e16518 (2021).