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Analysis and control of user engagement in personalized mobile assisting software for chronic disease patients

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Abstract
Existing solutions for patients support in mobile apps do not allow customization of the user interface to the needs of a particular user. It reduces the involvement of patients in the process of using the system. The lack of information leads to a decrease in the quality of treatment and the emergence of potential complications. The paper proposes a variant of a new interactive mobile patient support system. This technology allows patients to enter data about their health into a mobile application and track the dynamics in time, and doctors can monitor the course of treatment remotely. Models for tracking user engagement, such as the Cox proportional hazards model and the random effects model, are considered and demonstrated. The use of A/B testing to improve user experience is analyzed. The architecture of the mobile application, web application, and their interaction was developed and implemented. Risk assessment models for patients with chronic diseases have been built. The work of interactive user support technology within a single interactive system is shown. The developed approaches can be used to build a wide range of telemedicine solutions that support interaction with both medical specialists and patients within the framework of the 4P approach in medicine.

Keywords
mobile health application, remote assisting, mobile application, predictive models, user engagement, user experience, chronic disease patients

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УДК 004.5

Разработка технологии интерактивной мобильной поддержки пациентов с хроническими заболеваниями

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Аннотация
Предмет исследования. Существующие решения мобильной поддержки пациентов не позволяют адаптировать пользовательский интерфейс к потребностям конкретного пользователя. Это снижает вовлеченность пациентов в процесс использования системы. Недостаток оперативной информации приводит к снижению качества лечения и возникновению потенциальных осложнений. В работе предложен вариант новой интерактивной мобильной системы поддержки пациентов. Представленная технология позволяет пациентам вносить и отслеживать информацию о своем здоровье в мобильном приложении, а врачам получать возможность удаленно контролировать ход лечения. **Метод.** Рассмотрены и продемонстрированы модели отслеживания

вовлеченности пользователей, такие как модель пропорциональных рисков Кокса и модель случайных эффектов. Проанализировано применение A/B тестирования для улучшения пользовательского опыта.
Основные результаты. Разработаны и реализованы архитектура мобильного приложения и веб-приложение, а также их взаимодействие. Построены модели оценки рисков для пациентов с хроническими заболеваниями. Показана работа технологии интерактивной поддержки пользователей в рамках единой мобильной системы.
Практическая значимость. Разработанные модели могут быть использованы для построения широкого спектра телемедицинских решений с поддержкой взаимодействия как с медицинскими специалистами, так и с пациентами в рамках 4П подхода в медицине.

Ключевые слова
мобильное медицинское приложение, помощь на расстоянии, прогностические модели, взаимодействие с пользователем, пользовательский опыт, пациенты с хроническими заболеваниями

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Introduction

The technological revolution has impacted industries across the world, providing the opportunity to develop custom solutions for specialized needs. Medicine data sources have grown rapidly as a result of the spread of mobile devices. Mobile devices are perfect candidates for health data collection. They are equipped with many sensors, such as location services, accelerometers, barometers, cameras, heart rate sensors, included in some wearable models, pressure meters, and even electrocardiogram sensors. Due to their multiple capabilities and widespread use, mobile phones allow designing many successful healthcare applications.

Healthcare applications can be more patient-oriented by enhancing patient involvement and self-management features which are associated with significant health improvement, especially for diabetes and hypertension [1]. Effective methods of keeping the user's attention are important for this purpose. Thus, this article addresses patient engagement.

Although medicine deals with complex or sensitive data, doctors and patients can greatly benefit from taking advantage of medical mobile app development. Millions of people rely on their mobile devices to help them simplify their daily life. With a medical mobile app, more people will have access to a modern level of healthcare. However, there are still quite a few unresolved problems in the growing world of mHealth technologies. These include difficulties of integration with artificial intelligence [2], measuring patient engagement [3], and the problem of User Experience (UX) broadcasting of conventional mobile applications. These problems motivated this research.

Related works

There are many articles about mobile applications in medicine. Devi et al. [4] reviewed 90 studies and underlined the effectiveness of mHealth apps for HIV/AIDS patients. Kan et al. [5] described the healthcare management system with diet control and presented healthcare improvement effects for patients with diet control through apps. In this work, we focus on high quality UX and the interaction between the main components of the system. The importance of a good UX is confirmed by many studies. For example, Luna-Perejon et al. [6] showed that better accessibility and special techniques increase the usability of a mobile app for smoking cessation. Furthermore, there was no significant difference between age and gender groups in user satisfaction.

User Interface (UI) works closely with UX design. Both elements are crucial to a product. UX encompasses all aspects of the end-user interaction with the service or product. The concept of 'patient experience' has become the center of a growing global discourse on healthcare improvements. UX design focuses on the user's context and on emotional outcomes from using technology as opposed to task-accomplishment and usability.

There are many methods for improving the UI and UX. Additional information can be found using qualitative approaches involving focus groups and using A/B testing methods. Qualitative methods reveal more usability problems than questionnaires alone.

There are standardized methods to assess aspects of usability recommended by ISO 9241-11 [7]. These include the effectiveness of a system (the ability of a user to complete assigned tasks), efficiency (resources required to complete assigned tasks such as time), and satisfaction (user feedback). Understanding these aspects of usability is important when determining whether changes should be made in subsequent device iterations.

As health services become patient-oriented, offering a personalized and satisfactory experience is of utmost priority for healthcare providers. It is about feature variability or context-awareness. The designed system should gather clues about the situational environment and enable appropriate mechanisms of interaction between the end-user and the system, making it more intelligent, adaptive, and personalized.

Basic approach

The system includes 6 main components: mobile and backend application; machine learning approaches for prediction modeling, to find the probability of complications; analytics module with engagement models for building the best interaction scenarios; Electronic Medical Records (EMR) — the main source of medicine records; assistants — doctors and physicians.

This paper describes the role of each module and approaches to their integration in a unified system. Offering consumers the ability to see their laboratory results or predictions of complications on mobile devices can lead to greater levels of engagement. The two-tier client-server architecture was chosen as the base of the system architecture (Fig. 1). It provides multiple workstations (the mobile application on users' devices) with a uniform presentation layer that communicates with a centralized data storage layer (the server-side application).

The purpose of the study is to describe and partially implement a system of remote assisting for patients with various types of chronic diseases.

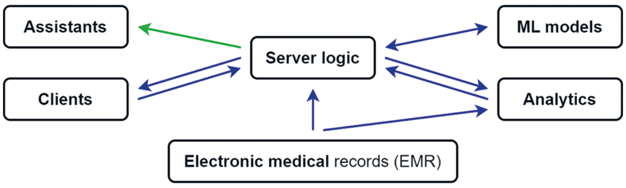

Fig. 1. The system architecture

Mobile application architecture and implementation

The Apple iOS operating system was chosen as a platform for developing the client application. The application logic was divided into three main modules: "Assays", "Symptom Tracker" and "Care Card" [8]. It works with Apple's HealthKit, ResearchKit, and CareKit platforms for the best integration with the iOS operating system ecosystem (Fig. 2, *a*). HealthKit provides a central repository for health and fitness data on iPhone and Apple Watch and is designed to share data between apps. The apps communicate with the HealthKit store to access and share this data with the user's permission. HealthKit can manage and merge data from multiple sources: wearable devices and applications of other developers. The app has 3 main modules (Fig. 2, *b*).

The "Assays" module provides data on all medical analyses of the user. The main screen is divided into sections. The "Symptom tracker" module collects all the tasks associated with the measurements and treatment plans.

The interface of the CareKit framework provides the ability to save the results in the database on a local device and to not worry about data safety. The "Care Card" module displays all the tasks that allow the user to control the course of treatment. The interface of the CareKit framework provides the ability to save the results in the database on a local device and not worry about data safety. ResearchKit and CareKit frameworks are used as assistants in collecting medical data[1].

The scheme of the interaction between clients, the server and its architecture are demonstrated in Fig. 3. All connections between clients and the server part work only through the Cloud Endpoints Application Interface (API). The Core is the main component of the server part. The components communicate and coordinate their actions by passing messages to one another. The distributed technology makes the connection of databases that are separate from each other.

Chronic patient modeling

The predictive models module uses data from mobile devices via application to train machine learning models and provide predictions to the user with certain accuracy. The following is a description of the model that predicts the probability of thromboembolic risk assessment complications, such as Atrial Fibrillation (AF) or thromboembolism.

Depersonalized patient data from EMR of the Almazov Center were used with the following fields: sex, age, clinical diagnosis, medical history. From the initial data (2 tables

[1] Apple Inc. ResearchKit and CareKit. 2022. Available at: https://www.apple.com/researchkit/ (accessed: 09.11.2022).

a *b*

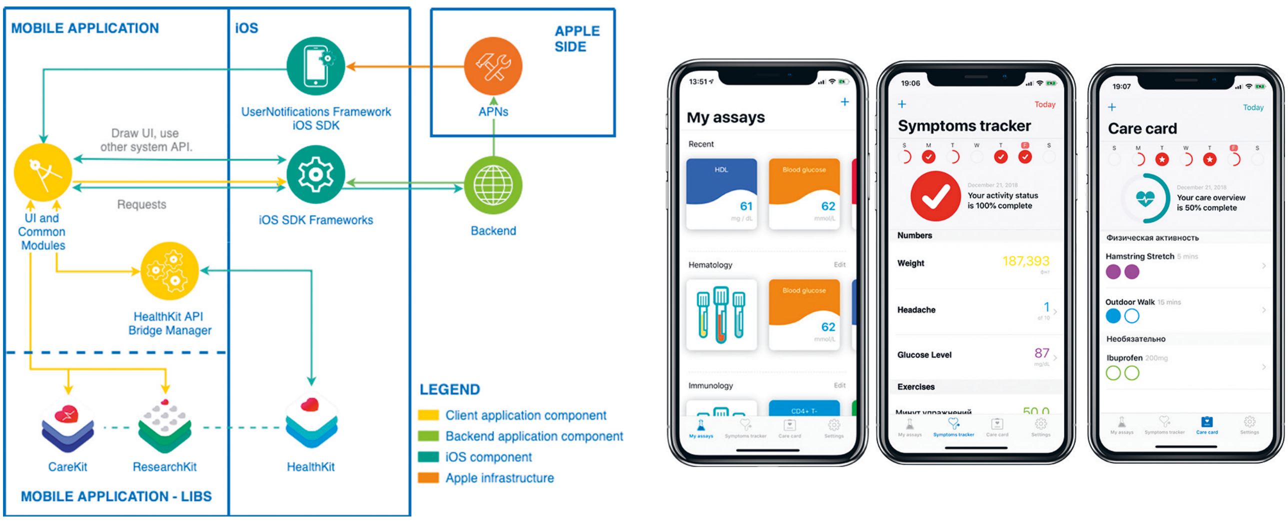

Fig. 2. Generalized common system interaction (*a*) and mobile application modules (*b*)

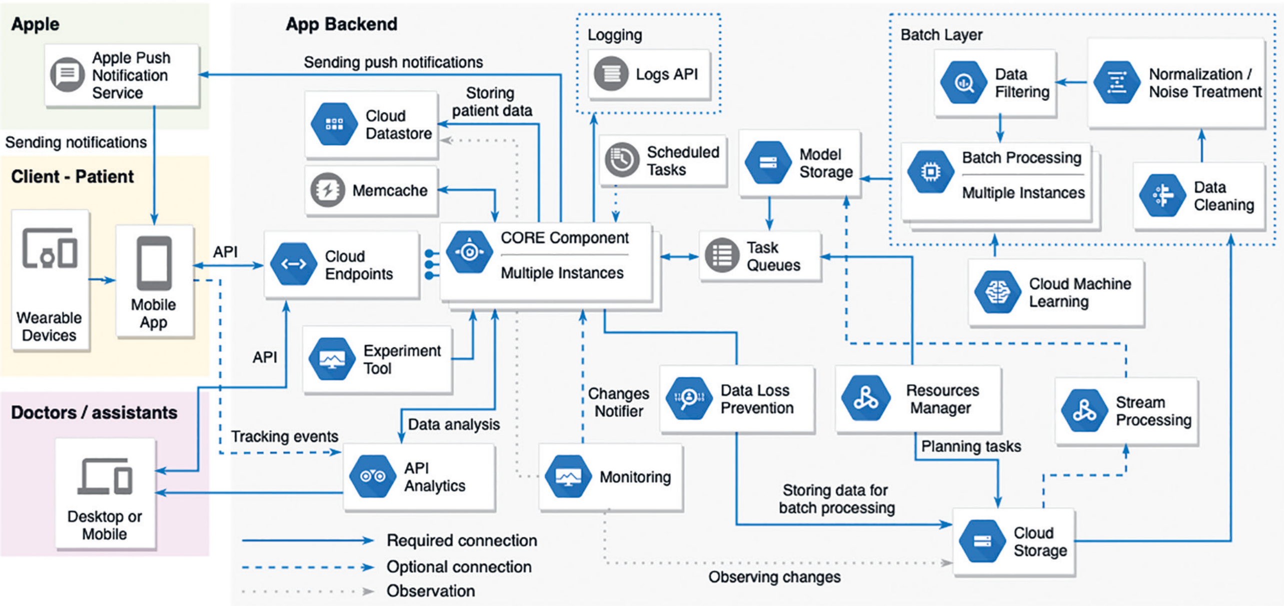

Fig. 3. Architecture of the server-side system

with patient data (date of birth, sex) with 5,722,189 rows and medical history data with 754,341 rows) 410,094 rows were selected (247,485 women and 162,609 men). Risk points are calculated using a $CHADS_2$ score. According to the European Society of Cardiology guidelines, "the $CHADS_2$ [cardiac failure, hypertension, age, diabetes, stroke (doubled)] risk index evolved from the AF Investigators and Stroke Prevention in Atrial Fibrillation Investigators criteria and is based on a point system" [9]. A. John Camm, (Chairperson. The CHA_2DS_2-VASc score is a refinement of the $CHADS_2$ score and extends the latter to include factors: age 65–74, female, vascular disease (Table 1)[1].

Percent distribution among patients' data with equal sex shows that the number of men in the selection is more for 2–4 risk points and women for 5 and more (Table 2).

According to statistics by age, the number of cases with risk points increases dramatically after 56 years for men (Fig. 4, *a*) and 65 years for women (Fig. 4, *b*).

With regards to arterial hypertension, men have a greater number of cases than women (32.64 % for women and 41.25 % for men) (Table 3). According to the age statistics, a huge increase in cases is observed after age 55 (Fig. 5, *a*). Concerning diabetes, men have slightly fewer cases than women (10.18 % for women and 8.28 % for men) (Table 3). More cases are observed after age 60 (Fig. 5, *b*). The constructed dataset includes the greatest number of heart failure diseases. Men have many more cases than women (26.59 % for women and 34.52 % for men) (Table 3). According to age statistics, the explosive growth of cases is observed after age 56 (Fig. 5, *c*). Vascular diseases have the biggest gap by sex features (27.42 % found cases for women against 43.15 % for men) (Table 3). Common age statistics are similar to heart failure diseases (Fig. 5, *d*).

In this paper, a classification model for predicting the likelihood of thromboembolic risk assessment complications such as atrial fibrillation or thromboembolism is given. Each unique patient record has an additional "Class" value: 1 if the patient already has atrial fibrillation or thromboembolism, 0 — if not. The primary classification is carried out using a keyword search corresponding to the main complications in the patient's medical history and by the international classification of diseases code, if available.

The 3 methods listed above were used to train the model. The resulting models were evaluated using the classifier model cross-validation control. As a result of the evaluation, it is obtained that the RandomForestClassifier and KNeighborsClassifier models have an accuracy value of 0.911, and the LogisticRegression model has an accuracy value of 0.912.

All models showed almost equal results, however, the random forest classifier (number of estimators equals 100, the function to measure the quality of a split is Gini) is faster and more precise, as shown on the ROC curve (Fig. 6), with AUC value equal to 0.8310.

Accuracy on training set: 0.789, on test set: 0.763, score: 0.764. Feature importance ranking shows that age and heart failures contribute the most to complications: age — 0.477, heart failure — 0.232, arterial hypertension — 0.129, vascular disease — 0.105, sex — 0.031, stroke — 0.014. The main results of the random-forest classifier are demonstrated in Table 4.

User engagement modeling

Keeping users engaged with a mobile health app is the key for its success, because the quality of care and the likelihood of complications often depend on it. Some studies show that deficiency of personalization can reduce long-term engagement [10]. Engagement is the level of

[1]Atrial Fibrillation Medical Management. UCSF, 2016. Available at: https://ucsfhealthcardiology.ucsf.edu/patient-care/clinical-services/electrophysiology-and-arrhythmias/patients/atrial-fibrillation-0 (accessed at: 15.10.2022).

Table 1. Thromboembolic risk assessment scale for patients with AF by CHA_2DS_2-VASc score

Risk factor	Points
Stroke, transient ischemic attack, or a history of arterial thromboembolism	2
Age more than 75 years	2
Arterial hypertension	1
Diabetes	1
Congestive heart failure/1 left venticular dysfunction	1
Vascular disease (a history of myocardial infarction, peripheral atherosclerosis)	1
Age 65–74 years	1
Female	1

Table 2. Data distribution of risk points by sex, a.u.

Sex	Risk points distribution							
	1	2	3	4	5	6	7	8
Female	0.298	0.193	0.148	0.149	0.150	0.044	0.016	0.004
Male	0.265	0.206	0.196	0.166	0.120	0.032	0.014	0.003

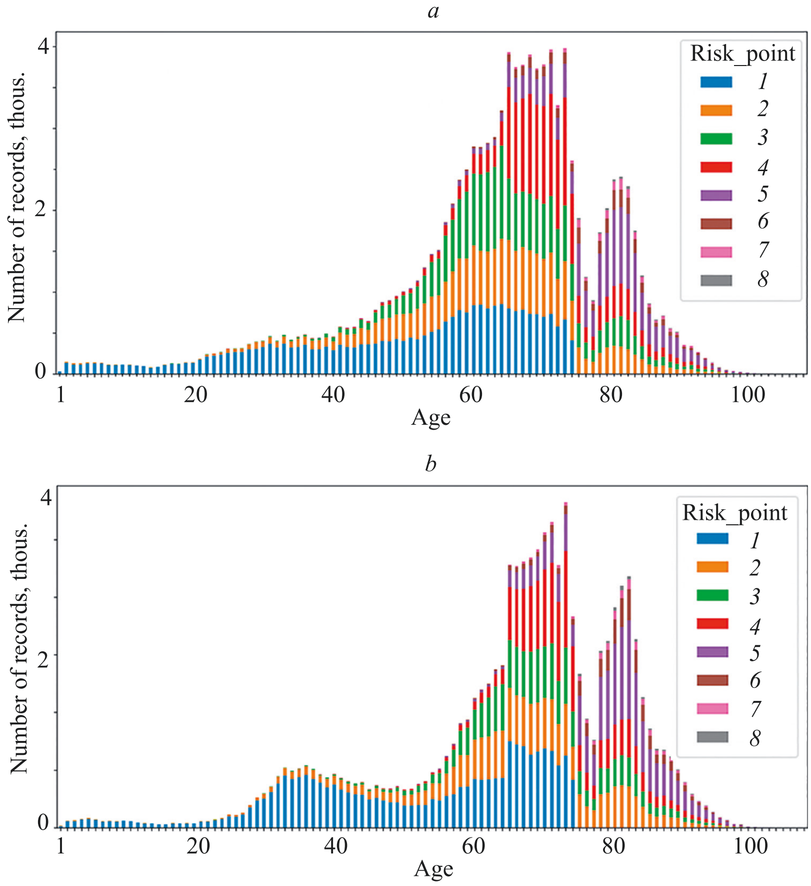

Fig. 4. Cumulative number of risk point cases by age — men (*a*) and women (*b*)

Table 3. Positive cases of different types of diseases in the total group of patients, a.u.

Sex	Diseases positive cases			
	Arterial hypertension	Diabetes	Heart failure	Vascular
Female	0.413	0.102	0.266	0.274
Male	0.326	0.083	0.345	0.432

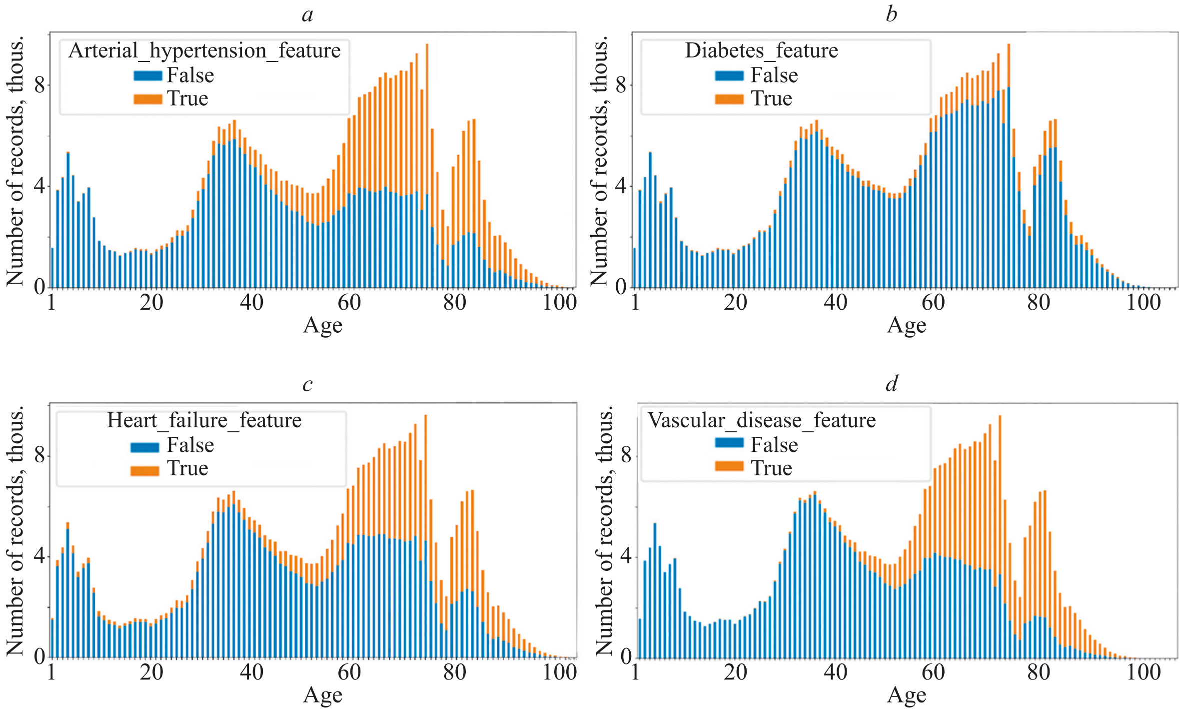

Fig. 5. Cumulative number of records with arterial hypertension (*a*), diabetes (*b*), heart failure diseases (*c*), vascular diseases (*d*) in medical history by age

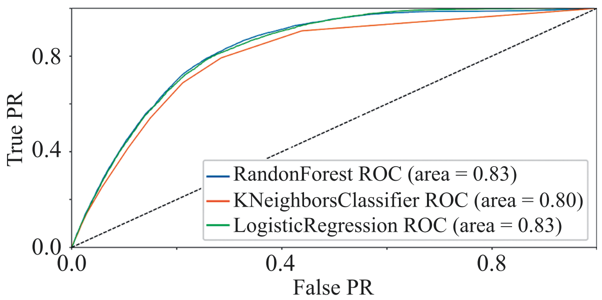

Fig. 6. ROC analysis of classifier models (where PR — positive rate)

Table 4. The results of the random-forest classifier

Class	Precision	Recall	F1-score	Support
0	0.80	0.70	0.75	7231
1	0.73	0.83	0.78	7100

user involvement with an application. High values of engagement metrics result in better patient satisfaction and clinical outcomes [11]. A successful UX design is incomplete without accurate A/B testing. An A/B test is a study of the impact of an independent variable on a dependent variable. It works by segmenting an audience into two (or more) groups and seeing how a variable affects user behavior. It is used to identify the best possible UX and deliver the best possible results.

One of the simplest engagement indices is called user engagement index (UEI). It compares the time of inactivity ($activity_x$ are dates, "today" is date of measurement) with time of engagement:

$$UEI = \frac{activity_{last} - activity_{first}}{today - activity_{first}}.$$

The most engaged user gets 1.0, inactive — 0.0. If $UEI > 0.5$, the user is considered engaged today. The UEI should be calculated for each feature and A/B test, if available. User engagement can also be defined by setting a threshold on the total number of actions (AT) performed within a time frame. A number of actions can show additional information about user interactions in addition to the UEI. To demonstrate the application, consider one A/B test for 10 users (2 groups of 5 people) for 10 days where the activity of using the survey function was measured on different screens (Table 5). Users will more often open the survey on the main screen. In the same way, we can apply the technique to other non-obvious situations to understand how a particular function affects the level of engagement.

Besides user engagement metrics, it is important to monitor changes in the app usage levels over time. For this purpose, a random-effects model was used. This model was chosen because random effects are evaluated with partial pooling (unlike fixed effects).

Applying the random-effect model to the data:

$$y_{it} = c_0 + c \times w_{i,t} + s_1 \times f_{1\ i,t-1} + \ldots + s_n \times f_{n\ i,t-1} + l_1 \times$$
$$\times w_{i,t} + \ldots + l_n \times f_{n\ i,t-1} \times w_{i,t} + X \times \delta + \varepsilon_{it},$$

where y_{it} — how many times the patient i logged in the application during the week t; w — the number of weeks since patient i admittance; $s_{1\ldots n}$ — the measure of the immediate short-term effects at the point of adoption; $l_{1\ldots n}$ — the measure of long-term effects over time; $f_{1\ldots n}$ — the frequencies of use of the app functions (n). The control variable X includes age, sex, number of visits to the

Table 5. Example of comparing the A/B test results

A/B test (number = 10, equal parts, length = 10 days)	UEI	AT
Health surveys on the main screen	0.80	7
Health surveys in the settings screen	0.54	3

doctor, disease type, trend of the latest health indicators (δ). The error $\varepsilon_{i,t}$ consisted of two components: disturbances $\eta_{i,t}$ and unobserved patient-specific characteristics v_i. The coefficient c means changes in the number of logins into the system with the session duration (bounce rate), c_0 is an initial value for logins. If the value is negative, it indicates that users reduce logins as they use the application longer.

Next, it is useful to perform the survival analysis to observe changes in the probability of stopping the application use. As an example, a simulation modeling of mobile application usage with 4 features was carried out for 50 days. Methods that imply specific shapes for the baseline hazard function contradict a key advantage of the Cox model — the ability to leave the distribution of the baseline hazard unspecified. So, the method by Harden and Kropko [12] was used for simulating durations without specifying a particular distribution for the baseline hazard function. At each simulation iteration, the method generates a unique baseline hazard by fitting a cubic spline to randomly-drawn points. This creates a wide range of shapes for the baseline hazard, including unimodal, multimodal, monotonically increasing/decreasing, and others. Then, the method generates a density function based on each baseline hazard and draws durations accordingly. Since the shape of the baseline hazard can vary significantly, this approach is consistent with Cox's inherent flexibility model. The survival model used the coefficients and available average values for 1439 patients from the paper by K. Lee et al. [13]. An experimental simulated data (number of patients = 30, number of events = 178), considering login and modules usage, showed that users mostly employed the app for the care card feature (39.33 % of total usage) and self-management (symptom tracker module — 26.4 % of total usage). The usage of the assay module makes up 17.98 % of the total usage. The support service module accounted for 16.29 % of the total usage (Table 6). This distribution demonstrated that the application had characteristic patterns of modules usage, and the care card module occupied was used the most, while self-monitoring has the second place.

The probability of continued use of the app decreased over time for all four modules, however, the slopes varied depending on the intensity of using a particular module

Table 6. Features usability distribution

Feature Name	Level, %
Assays	17.98
Care Card	39.33
Symptom Tracker (self-management)	26.40
Support	16.29

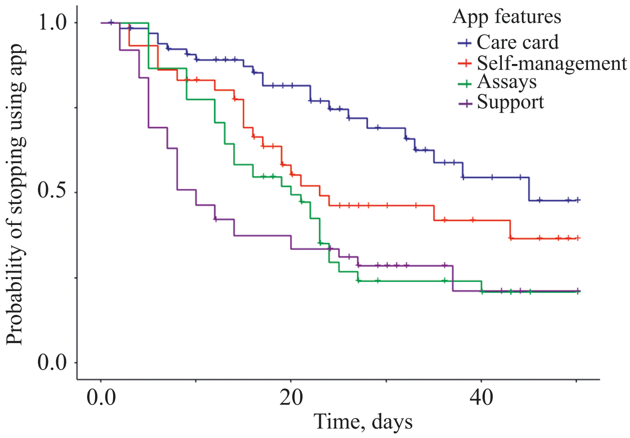

Fig. 7. Probability of usage cessation

(Fig. 7). The slope of the top line which represents a user who employed the care card module is flatter than others. The estimated survival rate suggests that 50 days after adoption, the probability of the regular use will be about 50 %. The symptom tracker feature was utilized less actively and lost more users, but the result at the end of the period is only slightly lower than the care card. It is worth noting that the value lies in the combination of the described methods, and the simulated experiment simply demonstrates one of them.

Discussion

Experiments have demonstrated the benefits of a combined approach to measuring user engagement. Using features with distribution statistics, user engagement, and the probability of usage cessation, it is clear which functions are more popular and which modules are needed by a particular patient at a given time. For example, a patient with headache and high blood pressure should have a support module and self-management feature in the foreground, and they are less interested in the assays module at a particular point in time. The UI of the mobile application adapts to achieve this goal. The described approach can be extended by integrating other machine learning models that solve different problems including other chronic diseases and their complications. It is possible to use other ways to measure user engagement and add additional submodules for analytics and data analysis. The modular architecture of the system provides for the rapid replacement of components with similar structures, but which solve different tasks.

Conclusion

Usability and engagement are central to the design of any service, especially one related to health. Mobile health applications should be aligned with users' goals and behaviors. User interface and user experience are crucial to the level of user engagement which is the key to success. This study demonstrates the importance of working closely with UX which is related to experiments (A/B, A/A testing). The described combination of technical, mathematical, and statistical methods is aimed at improving the quality of using the application, making healthcare more personalized. This work shows how health providers can measure patient engagement and improve the quality of care within the mHealth service. Future development of mobile health apps based on user retention practices need to consider problems for better user satisfaction.

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