Recommendation System for Leisure Time-Management in Quarantine Conditions

Oleh Veres[1], Pavlo Ilchuk[1], Olha Kots[1], Yana Levus[1] and Olha Vlasenko[2]

[1] Lviv Polytechnic National University, Stepana Bandery str. 12, Lviv, 79013, Ukraine
[2] Osnabrück University, Institute of Education Science, Heger-Tor-Wall 9, 49074 Osnabrück, Germany

Abstract

The paper describes the problems during quarantine restrictions and how this affects the psycho-emotional health of the person. The need to adapt and modify the usual forms of leisure activity to the new format has been determined. The most famous modern information systems, providing entertainment services are narrow-purpose systems. They generate recommendations related to media services. Methods of providing recommendations have been studied. A tree of goals was built to solve the problem situation. Alternative means of implementation of the information system are considered. Using the Analytical Hierarchy Method, the optimal type of system for the implementation of the proposed solution was chosen – a recommendation system. The algorithm of work of the recommendation system of free time during the period of forced stay at home is described. The mechanism of weight optimization in the weighted hybrid recommendation algorithm was used to provide recommendations. When a user's portrait is created, the method of the personality type indicator is used. Using the UML language tools, a conceptual system model has been designed. For realization of the prototype of a mobile application of the system language programming Java, JavaScript, frame react Native is chosen. To work with the database the MySQL database management system has been selected. An example of using the system as a mobile application is given. The main stages of interaction of the user with the recommended system of free time during the period of forced stay at home are described.

The work of the recommendation system is aimed at mitigating the negative consequences on the psycho-emotional state of a person who is in the conditions of forced quarantine. The special feature of the recommendations of the developed prototype is to offer, in addition to passive activities, active actions that take into account the peculiarities of each user.

Application of the system is not limited only to quarantine. The services of the system will be appropriate for people with disabilities, in the case of physical injury transfer or liquidation, which led to temporary immobility.

Keywords [1]

Quarantine Conditions, Methods of Recommendations, Recommendation System, Leisure Time-Management

1. Introduction

Global access to any information is more often considered an advantage than a disadvantage. A person has the opportunity to view many alternatives, compare them and choose the best option for himself. Being in such a constant flow of alternative offers has led to the fact that working out useful positions on your own is not an easy task.

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EMAIL: oleh.m.veres@lpnu.ua (O. Veres); pavlo.g.ilchuk@lpnu.ua (P. Ilchuk); olha.o.kots@lpnu.ua (O. Kots); yana.levus.msa.2020@lpnu.ua (Y. Levus); olha.vlasenko@uni-osnabrueck.de (O. Vlasenko)
ORCID: 0000-0001-9149-4752 (O. Veres); 0000-0003-4636-2309 (P. Ilchuk); 0000-0001-7123-3635 (O. Kots), 0000-0003-3702-1510 (Y. Levus); 0000-0001-7258-2108 (O. Vlasenko)

Recommendation systems help solve the problem of such information overload [1]. The main task of the recommendation system is to provide personalized recommendations to the user that take into account his preferences when choosing items (goods, objects, or services). Recommendation algorithms can deliver useful suggestions to users, such as movies, books, videos, music tracks, travel trips, clothing, sports training, potential social media contacts, etc.

2020th has changed all areas of people's lives. This is due to the COVID-19 pandemic and quarantine restrictions, including lockdown in many spheres. Research by the World Health Organization has shown that the most optimal way to reduce the rate of spread of the dangerous virus is to stay at home to avoid contact with people. The governments of most countries of the world have decided to implement quarantine restrictions on their territories. This involves the temporary closure of many structures and institutions for an indefinite period and, if possible, transferring their activities to a remote mode. The level of relevance of recommendations for spending time outside the home is beginning to decrease.

As a result, people's usual way of life has completely changed. Work and studies have moved to an online format. Meetings with friends and relatives are via video communication. Classes with a sports coach are organized through a special online platform or using video communication. Instead of going to the cinema, people subscribe to media services to watch TV programs and movies. It was possible to adapt some leisure activities to the new reality, and for others, people had to look for alternatives. Being in a constant flow of alternative offers has led to the fact that working out useful positions on your own is not an easy task.

2. Analysis of Recent Research and Publications

In the COVID-19 conditions, the quarantine restrictions and the psycho-emotional state of every person are negatively affected [2, 3]. One of the public health measures to minimize the spread of the COVID-19 virus is the implementation of extended lockdown periods. Access to all infrastructure is limited or unavailable, and people are advised to stay within their homes. Usual daily tasks and activities in various spheres of life become unattainable. The consequences of such instantaneous and unexpected changes are negative, as they force people to adapt to new everyday realities.

With the spread of quarantine measures in most countries, there were increasingly frequent calls from doctors and scientists to pay attention and study the impact of the lockdown on the psychological health and well-being of the people [2]. There is a general need to understand what exactly a person is experiencing inside himself during this period, and how it is possible to support health during the restoration of normal life because it can take months or years.

The study on the consequences of the H1N1 flu did not reveal a negative psychological effect of quarantine [4]. However, in the case of the SARS epidemic, stress scores for post-traumatic stress disorder were recorded to be 4 times higher in those persons who were in isolation than in those who do not have restrictions [5]. Studies in India have similar results [6], and studies in China have found that people have increased symptoms of depression and anxiety symptoms and may experience negative psychological effects as a result of the COVID-19 pandemic [7].

A special term "loneliness epidemic" was implemented [8]. It is characterized not only by the fact that a person could not physically contact others for a long period of time: relatives, friends, peers, colleagues, neighbors, etc. It means that person feels boredom and frustration, and feelings of isolation are also associated with the loss of the opportunity to engage in most of the usual activities related to both professional and personal spheres of life.

It can be assumed that during the COVID-19 pandemic 38% of people felt tired or lacked energy; 36% had sleep disorders, 25% felt helpless, depressed, or hopeless; 24% had difficulty concentrating, 43% felt nervous, anxious, or worried; 36% reported that they could not stop worrying, 35% noted that it is difficult for them to relax [9]. In the United Kingdom, studies found similar results [10]. Among participants, 25% felt that their anxiety and depression had significantly worsened during the lockdown, and 37.5% met clinical criteria for general anxiety, depression, or anxiety (April 2020).

The COVID-19 pandemic period is characterized by the growing role of information technologies, the increase in the number of IT products, and their active distribution. The first quarter of 2020 was the most successful in history for app stores [11]. More than 31 billion new apps were downloaded and more than \$23.4 billion was spent by customers on purchases related to mobile apps. IT solutions are popularized in new industries that completely change them. Thus, the gym can now be replaced by a selection of online workouts in a fitness application, a visit to the cinema – by renting a movie in a media streaming service, offline studying or work is changed to a remote and online type, etc.

The lack of previous experience of being in a prolonged quarantine gives rise to uncertainty, fear, and anxiety. Therefore, a person is searching for ways to abstract from these problems, options for adapting to new living conditions, and diversifying activities. Support in solving this problem is provided by information systems that expand human capabilities, help make better decisions, and provide valuable recommendations based on the specifics of a particular user. An important factor is that users expect a personalized experience from such systems, and to receive services that take into account preferences, behaviors, and other characteristics.

2.1. Overview of algorithms used in recommendation systems

The need for algorithms that can filter items according to their relevance to the user arose along with the spread of e-mail usage as one of the main ways of communication between colleagues and employees of institutions. The PARC Research Center created one of the first recommendation systems that filtered e-mails based on topics that the user indicated as important [12].

Recommendation systems are one of the most popular applications of intelligent data analysis and machine learning in the field of Internet business. They analyze the behavior of users of the Internet service, after which they give a quantitative and qualitative assessment of users' preferences. The objects of recommendations can be products in the online store, a set of the Web site sections, media content, or other users of the Web service.

Modern recommendation systems can be classified by filtering methods, namely: collaborative filtering, content-based filtering (including demographic filtering, knowledge-based filtering), and hybrid filtering.

Collaborative filtering uses the known ratings of users' groups to predict the unknown preferences of another active user. It is supposed that data on past interactions is sufficient to detect similar users and/or similar elements and, accordingly, make predictions based on similar estimates [13]. Collaborative filtering methods include three main approaches: memory/heuristic-based, model-based, and hybrid. A key advantage of collaborative filtering approaches is that they do not rely at all on element content analysis or user characteristics. It is not required to study the element in order to understand it, search for similarities, and build recommendations. The more active users interact with the elements, the more accurate the new recommendations become [14].

Content-based filtering uses information about the object's properties. The idea of content-based filtering is that users give similar preferences to items with similar content. Content-based filtering can be used in such systems, where the presence of descriptive data is assumed in advance [15].

Demographic filtering provides recommendations based on the demographic (for example, age, profession) profile of the user [15]. Recommended products can be created for different demographic niches by combining the ratings of users in those niches.

Knowledge-based filtering offers recommendations based on conclusions about the needs and preferences of users, their previous selection of elements, etc. [15].

The combination of collaborative filtering and content-based filtering is called *hybrid filtering* [15]. It combines collaborative filtering with demographic filtering, content-based filtering, or both demographic filtering and content-based filtering. This method is the most promising for solving problems of predictive recommendations.

2.2. Analysis of available information systems in the field of providing leisure time-management recommendations

Basic information about information systems that generate recommendations to users is presented in Table 1. In terms of the problem of adaptation to quarantine conditions, the above analogues are distinguished by certain disadvantages.

Table 1
Overview of Software Solutions

Title	Scope of Application	Features
Flinder	Online service of recommendations for activities outside the home	Activity recommendations are based on received information about location, time of day, and weather.
Gravy	Online service of recommendations for activities outside the home	Activity recommendations are based on the user's mood. A page with trending recommendations is created.
YouTube	Video hosting	Recommendations of two types: global trends and personal recommendations – videos that are suggested based on a particular user's past viewings.
Netflix	Video content provider	Movie and TV series recommendations are based on the use of machine learning, making them more accurate over time for each user. Using extremely precise genres and user groups.
Google Calendar	Online planner-calendar	There is absolutely no feature to generate recommendations. The user independently fills the calendar with various events, tasks, etc.
Microsoft To Do	Online "To-do" list	There is no feature to generate recommendations. The system offers to add to the current list tasks that were not marked as completed on previous days. The user independently enters various tasks into the list. Can receive a response based on a similar request from another system user.

The first two systems did not adapt to COVID-19 conditions: the proposed activities related to events held in public places. As a result, their recommendation bases became significantly smaller in volume, and one of the applications stopped functioning altogether.

YouTube and Netflix are distinguished by significant achievements in the modification and development of recommendation algorithms, but they are characterized by a narrow specialization in video and audio content. In lockdown conditions, such systems are not able to fully satisfy the needs of a person. The functioning of these systems was not foreseen for the number of simultaneous users' needs, as it happened during the pandemic. As a result, users from different countries faced slow connection problems or no access at all for some time.

Google Calendar and Microsoft To-Do don't have built-in recommendation algorithms.

Netflix is an American company that provides paid services for streaming movies and series. With the transition to online services, the value of the company in terms of the trends in the methods of recommendation systems began to grow rapidly. So the Netflix owners researched based on the analysis of user behavior that the recommendation system has about 90 seconds to form alternatives to help the user find an interesting feed before he leaves the platform and turns to another service. That's why Netflix's core value proposition is to provide relevant recommendations to its customers. Recommendation systems include various algorithmic approaches: reinforcement learning, neural networks, causal model, probabilistic graphical models, factorization of preference matrices, etc. [16].

YouTube is Google's social network based on sharing videos between users. In 2008, the company developed a recommendation system for the platform. The system compared users and looked for similar behavioral characteristics, and a system for rating videos by popularity was implemented. In 2011, they implemented the analysis of other user actions: clicks, viewing time, systematic surveys, likes, and sending videos to other users or to other platforms. Currently, YouTube's recommendation algorithms have two goals: finding the correct video for each user and encouraging them to watch it as long as possible [17].

For YouTube, as for Netflix, the rule works: the more often a user accesses the services of the platform, the better it understands him and provides more accurate recommendations.

2.3. Main Objectives of the Designed Information System

There is a need to manage free time during periods of forced stay at home. It is necessary to find a solution that can select options for spending time based on the characteristics of each person or general trends. Therefore, the research and development of an information system for leisure time-management, in which the recommendation method will be used to offer users relevant suggestions for activities while staying at home, is very relevant.

The result of the information system usage should be a set of relevant offers to the user for spending free time. Increasing the accuracy level of recommendations should be ensured by analyzing the user's activity in the system, interacting with its elements, and using and modifying the methods of recommendation systems. With the help of a systematic user survey (as in a certain defined period or randomly), data related to the user's preferences will be accumulated. In addition, it is necessary to analyze and monitor user behavior within the system, determine its model, and recognize interdependencies. In this way, the purpose of the recommendation system from the user's viewpoint is achieved.

High-level user needs are captured in a list of user story statements. This method of formulating requirements is presented in the format of sentences "*As a user of (specification of type), I want (goal) to (use)*". User or customer statements are used to describing user requirements, which provide an understanding of exactly how a person will use the system and what results are expected. The main user stories related to the *recommendation system for leisure time-management in quarantine condition*s have been developed:

- "As a user, I want to be able to familiarize myself with the purpose and functions of the system in order to decide whether the system will help me in solving my problems";
- "As a user, I want to register in the system using an e-mail to access the system functionality";
- "As a user, I want to receive recommendations for activities to diversify my daily routine";
- "As a user, I want to contribute to the construction of my psychological portrait in the system in order to be able to receive useful and interesting recommendations on types of activities in order to try new activities";
- "As a user, I want to take surveys to get better recommendations on the time of the event";
- "As a user, I want to record my achievements to monitor my daily progress";
- "As a user, I want to evaluate recommendation suggestions to eliminate irrelevant recommendation positions".

Methods of system analysis were applied to analyze the problem situation and justify the choice of the type of information system for leisure time-management during the quarantine period [18]. To achieve the general goal, a goal tree was developed. The main task is to create an information system for time-spending during periods of forced stay at home. The system quality criteria are:

- *reliability* – the ability to maintain the appropriate level of performance under the set conditions during the specified period;
- *security and privacy* – ensuring the implementation of security and data security protocols;
- *availability* – the use of resources and potential of the system is possible in the absence of a longer than specified wait;
- *efficiency* – the ratio under certain conditions of the software productivity level and the amount of resources used to ensure the its productivity level;
- *renewability* – efforts and time resources, which are necessary for the system to respond to changes caused by non-standard operating situations;
- *error management* – processing of errors that occur during system operation, providing sufficient feedback to the user;

- *clarity* – refers to the effort required by the user to achieve the goals of using the system;
- *relevance* – providing the most relevant results for user requests regarding recommendations;
- *responsiveness* – sufficiently fast processing of the user's request and providing an answer to it.

It is necessary to determine which type of information system would be the most appropriate to use for leisure time-management. Alternatives considered:

- A_1 – Decision Support System (DSS);
- A_2 – Recommendation System (RS);
- A_3 – Content Management System (CMS);
- A_4 – Management Information System (MIS).

The Analytical Hierarchy Method was used to compare and evaluate alternative types of information systems [19-21]. According to the built hierarchy tree, calculations of priority vectors were carried out, as well as hierarchical synthesis was carried out with the aim of determining the priority vector of alternatives in relation to their criteria and aspects of the hierarchy. Analysis of the received vector values shows that the most appropriate option for implementation of the information system of leisure time-management during the quarantine period is an alternative A_2 – the development of the recommendation system.

2.4. Description of the working mechanisms of the recommendation system

Any recommendation system goes through the following phases of recommendation formation:

- data collection phase;
- learning phase;
- phase of formation of recommendations (or predictions).

The recommendation system for leisure time-management in quarantine conditions will work according to this principle (Figure 1).

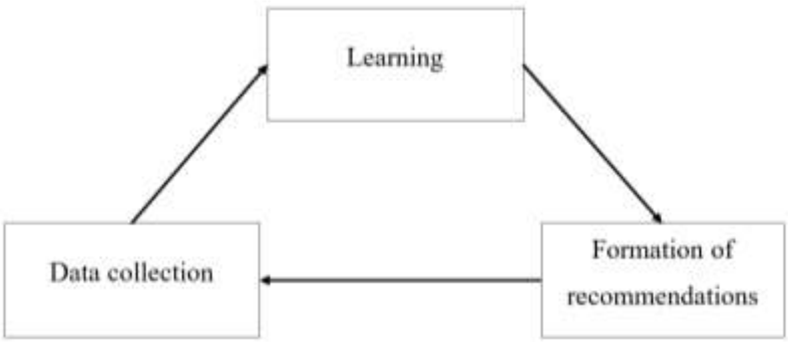


Figure 1: The main phases of the recommendation system

The first phase consists of gathering information about users to create a user profile or model for making recommendations, including user attributes, behavior, or the content of the alternatives that the user accesses [22]. A recommendation system needs to know as much information as possible about the user in order to provide reasoned recommendations. During the user's initial interaction with the recommendation system for leisure time-management in quarantine conditions, the user must complete a questionnaire. This will enable the recommendation system to obtain basic data to initiate the process of building a portrait, i.e. a model of the user.

When creating a user portrait, the Myers-Briggs personality type indicator method [23] was used. A personality type is formed by a combination of four preferences, which are formed on the main four scales:

- E-I scale (extraversion – introversion) – indicates what consciousness is directed towards;

- S-N scale (specificity – intuition) – indicates how information from the outside is perceived;
- T-F scale (thoughts - feelings) - indicates the basis of which decisions are made;
- J-P scale (judgment - acceptance) - indicates which methods of preparation for action will be used.

The application of this technique in the recommendation system will make it possible to more fully understand the user's portrait and predict the preferences of other users.

Recommendation systems rely on different types of input data to obtain ratings from the user. The most convenient and easiest method of data collection is explicit feedback. It does not involve determining the preferences of users based on their actions, and also ensures transparency of the recommendation process, which leads to a slightly higher quality of recommendations and more trust in recommendations [24]. Implicit data collection about the user occurs through the formation of an indirect conclusion about the user's preferences through observation of his behavior in the system, and interaction with its elements. Unlike explicit feedback, implicit feedback reduces the burden on users by determining their preferences based on their interaction with the recommendation system. Implicit data about preferences may actually be more objective because there is no bias, no self-disclosure issues, or the need to maintain an image for others [24]. The method is characterized as less accurate compared to explicit data collection.

The strengths of both implicit and explicit feedback can be combined in a hybrid system to minimize their weaknesses for the best user data collection system. This method is used in the recommendation system for leisure time-management in quarantine conditions. Implicitly collected data will be used to predict and develop preference recommendations, as well as to verify explicitly provided ratings. The data collected in both ways complement each other and constantly update the user profile. The obtained data is distinguished by a high level of accuracy, which will make it possible to build correct user models – and as a result, form more relevant recommendations.

A user profile in a recommendation system for leisure time-management in quarantine conditions is a set of personal data of each user, namely: interests, user preferences, habits, temperament, and interaction with the system. The user profile is used to obtain the data needed to build the user model. Thus, a user profile describes a simple user model. The success of any recommendation system largely depends on its ability to represent the user's current interests. Accurate models are indispensable for obtaining relevant and accurate recommendations using any method.

During the second phase, the learning phase, learning algorithms are applied to the collected user data. Thanks to this, the system can recognize patterns of user behavior and preferences in a certain situation [25]. The deployment of such an algorithm is required to ensure that the built model can filter user attributes based on the collected data. The goal of the training phase is to ensure that the recommendation system is trained to adapt to new data in order to optimize and increase the accuracy of the provided recommendations (prediction of preferences).

The phase of providing recommendations consists in forming recommendations for the user with the help of the applied method of providing them. In order to avoid certain limitations of "pure" recommendation systems and to minimize the problems created in providing recommendations, hybrid methods are used [26-30]. The idea is that a combination of algorithms will provide more accurate and efficient recommendations than a single algorithm since the shortcomings of one algorithm can be overcome by another algorithm.

Therefore, the weighted hybrid method calculates the prediction score as the results of all the recommendation approaches, treating them as variables in a linear combination. Assuming that there are k recommendation approaches to be combined using a weighted strategy, the prediction score of user m to item i can be calculated as:

$$p_{m,i} = \sum_{f}^{k} \sigma_f p_{m,i}^{(f)} \ , \tag{1}$$

where σ_f –weight of an algorithm $p_{m,i}$.

Since two recommendation approaches will be combined, then $k = 2$. Then we get:

$$p_{m,i} = \sigma_1 \times p_{m,i}^{(1)} + (1 - \sigma_1) \times p_{m,i}^{(2)}. \tag{2}$$

And the optimized weight can be obtained with the help of calculations [29]:

$$\sigma_1 = \frac{\sum_m \sum_i \left(p_{m,i} - p_{m,i}^{(2)}\right)\left(p_{m,i}^{(1)} - p_{m,i}^{(2)}\right)}{\sum_m \sum_i \left(p_{m,i}^{(1)} - p_{m,i}^{(2)}\right)^2}. \tag{3}$$

It is the weighted hybrid method that is used in the recommendation system for leisure time-management in quarantine conditions (Figure 2).

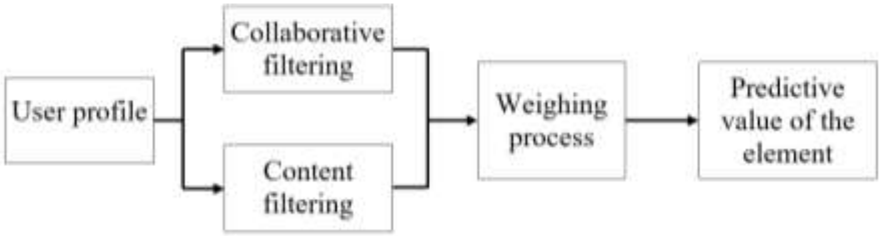


Figure 2: Weighted hybrid recommendation method

The results of the different recommendations are combined to create a list or prediction by integrating the scores of each of the methods used, according to the linear formula (2). Initially, recommendations from collaborative filtering and content filtering are given equal weight. As the predictions are confirmed or denied, the weights are adjusted [30]. The advantage of the weighted hybrid method is that all the strengths of the recommendation system are used during the process of providing them in a simple way.

2.5. Conceptual model of the recommendation system

The development of a conceptual model of the recommendation system ensures the identification of its various entities and their possible interaction [31-35]. However, the identification of such requirements at this stage provides an opportunity to save resources at later stages of the development life cycle, where the disclosure and unplanned implementation of new components of the recommendation system requires more effort and resources.

When developing the conceptual model of the system, UML (Unified Modeling Language — unified modeling language) diagrams are built, which are designed to simplify the understanding of the created project of the information system [36]. Diagrams increase project support and facilitate documentation development. To describe the functions of the system, a use case diagram was developed (Figure 3). It is a representation of the user's interaction with the recommendation system, which depicts the relationship between the user and various use cases in which the user is involved.

There are three actors in the system: "User" and "Guest", which are connected by a generalization relation, and "Administrator".

"User" is a person who has successfully logged into the system. "User" has access to the entire system and can use all the functionality of the system. Unlike the "User", the "Guest" has the right only to get acquainted with the functions of the recommendation system. However, after authorization, the "Guest" receives all the rights of the "User". The "User" has the opportunity to create a profile – based on the received data, initial recommendations will be made. The "User" can get a recommendation by selecting a leisure category, and scrolling through the list of recommendations is possible. The "User" can also view not only his own recommendations but also go to the "popular" category. Any recommendation from the "User" list can be marked as fulfilled. Then it will be available for viewing in the achievement diary. In addition, the "User" can make changes to the parameters of his own profile, that is, manage his account.

The following usage options have been created: "Create a profile"; "Pass the questionnaire"; "Scroll through the list of recommendations"; "View "popular"; "Get a recommendation"; "Choose a category"; "Reject a recommendation"; "Choose a recommendation"; "Rate the recommendation"; "Mark the recommendation as "done"; "View diary of achievements"; "View earned awards"; "Get acquainted with the capabilities of the system"; "Manage account"; "Delete account". The use options "Create a profile" and "Pass a questionnaire" are connected by the relation of inclusion since the creation of a profile involves an additional completion of a questionnaire. The use cases “Scroll through the list of recommendations” and “View “popular”, “Scroll through the list of recommendations” and “Rate the recommendation” are connected by an extension relation, that is, the functional behavior of the second use case is not always used by the base one. The “Get a recommendation” and “Choose a category” use cases are connected by an inclusion relation, these steps are somewhat dependent. The “Get a recommendation” and “Reject a recommendation” use cases are related by extension, because the user can in some cases, but not always, at his own discretion reject the recommendation due to its impracticality for him.

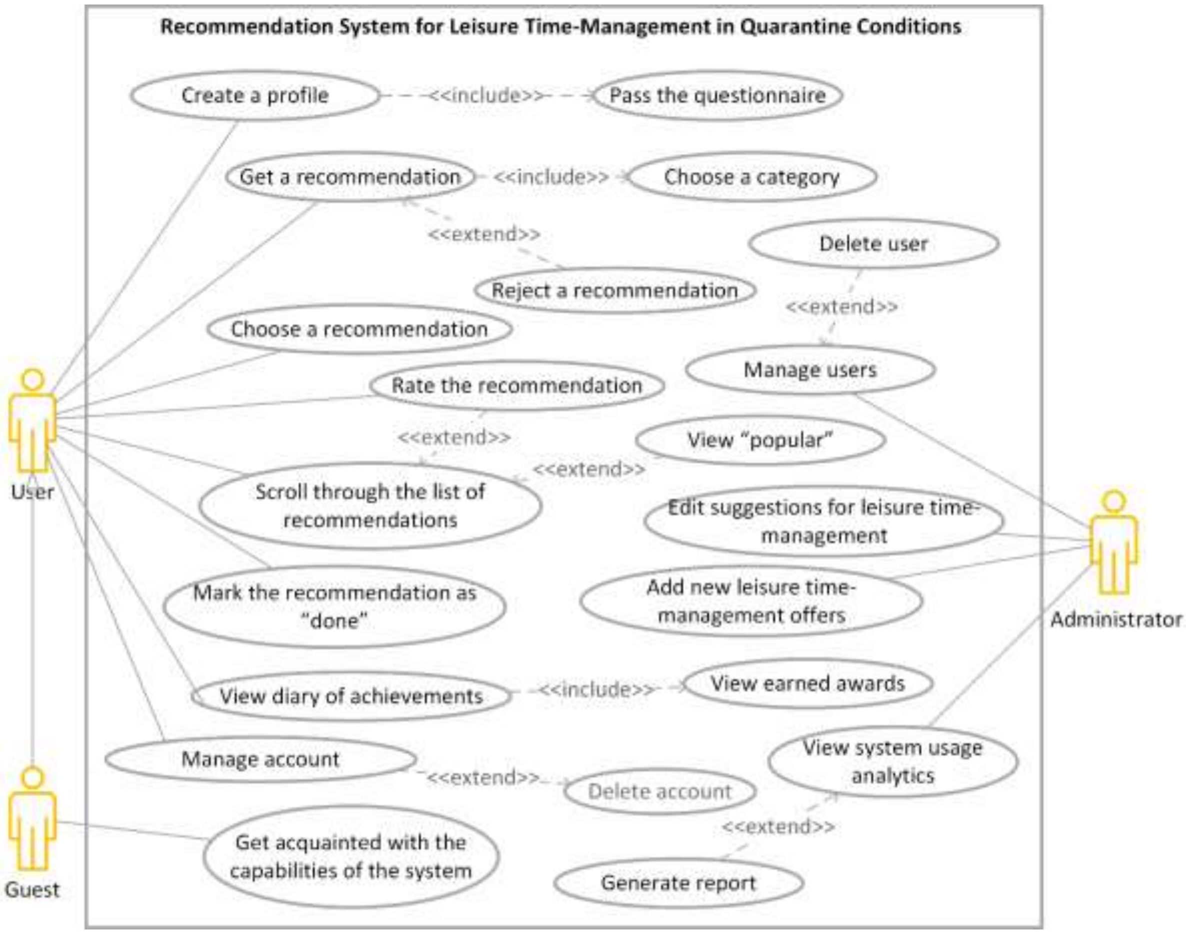


Figure 3: Use case diagram

“Administrator” is an actor who is responsible for setting up the recommendation system, managing users, and can receive analytics related to user interaction with the system. “Administrator’s” multiple use cases are: “Manage users”; “Delete user”; “Edit suggestions for leisure time-management”; “Add new leisure time-management offers”; “View system usage analytics”; “Generate report”.

Figure 4 shows the activity diagram for the designed system.

With the help of an activity diagram, you can describe the dynamic system behavior. In this case, high-level user actions are modeled, including process coordination to achieve the main goal of using the system.

As soon as the user successfully enters the system, the following actions will be available to him:

- “View “popular” - a list of recommendations that can be noted with a high level of popularity among users during a fixed period of time. Recommendations with the highest ratings, with the highest concentration of users on activity in a certain time period, fall into this category, that is, those where the system has recorded a lot of interest from various users;

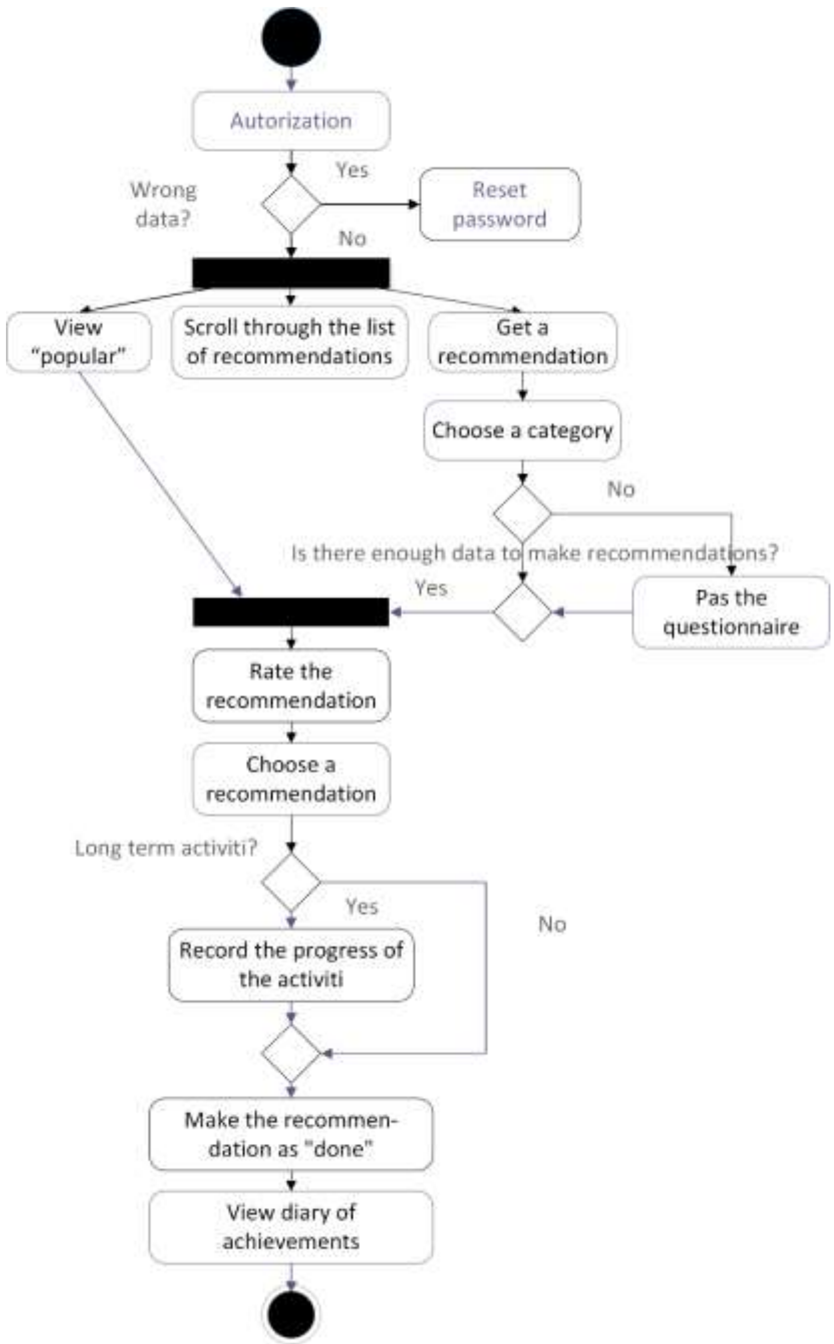


Figure 4: Activity diagram

- "Scroll through the list of recommendations" - a short list of personal recommendations generated by the system, based on available data about the user's interests and the results of their processing;
- "Get a recommendation" - a direct request from the user to receive a recommendation that is different from those that already exist in the list of personal recommendations. Here, the user needs to choose a category and, if necessary, complete a short questionnaire to provide the system with more data to provide a relevant recommendation;
- "Rate the recommendation" - the user can rate any recommendation, regardless of whether he is in the process of implementing it, has already completed it, or has never implemented it. This will speed up the process of cutting off irrelevant recommendations to the user. It is not possible to edit the provided rating;
- "Choose a recommendation" - with this action, the user informs the system that he is ready to perform the recommended activity. The system, in turn, provides the user with the

necessary content and feedback related to the selected activity. If the activity is characterized by a long period of systematic execution, then the user will be able to record progress;

- “View diary of achievements” - after the user completes a certain activity, it will be recorded by the system in the personal diary of achievements.

The state diagram for the designed information system of leisure time-management during the quarantine period is shown in Figure 5. The model of system behavior from the point of view of forming and providing recommendations for the user is illustrated here.

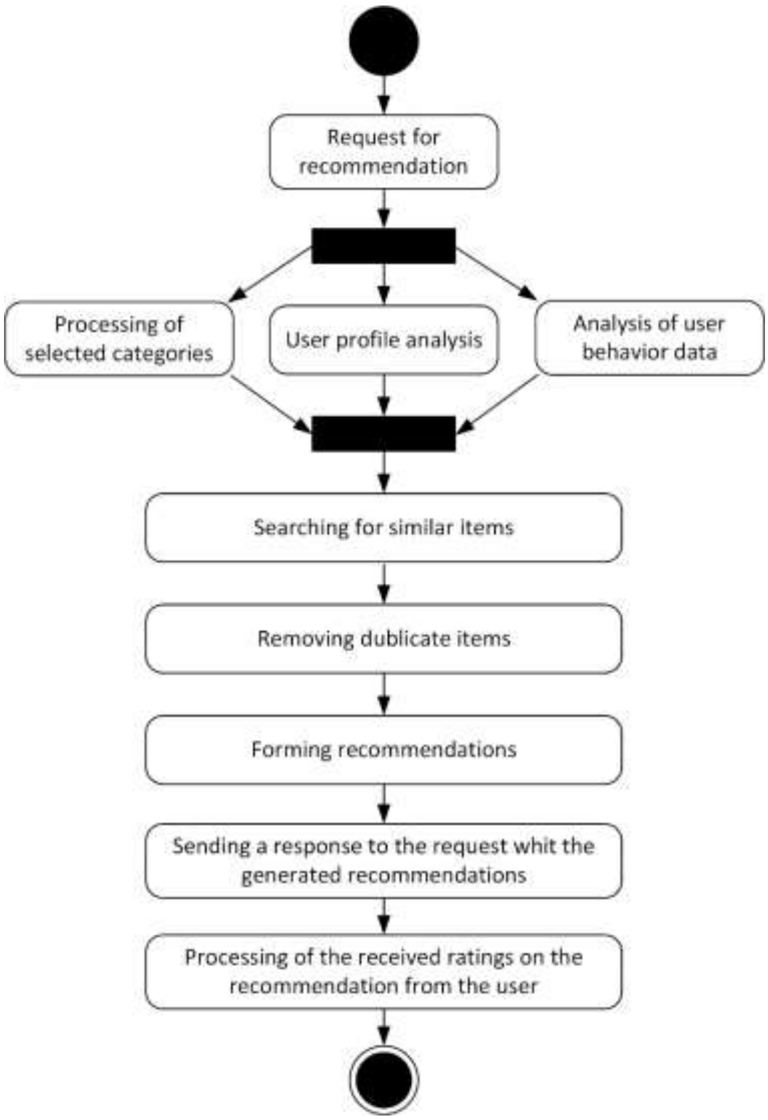


Figure 5: State diagram

The process involves users who have successfully logged in with their accounts. When creating a user profile, a person gives general information about himself. After that, the mandatory step is to complete the questionnaire. The goal is to start the process of forming a psychological portrait of the user. Recommendations are built on the basis of user profile data and completed questionnaires. It is also an important step for the user to select the categories of time-spending at home directly when selecting the function of recommendation receiving. This request from the user is processed by the recommendation module. The user needs to send a request to get a time pass recommendation. The system starts processing the request by analysing the selected category, user profile, data on his behavior, and portrait. Then the recommendation methods search for similar elements (meaning the similarity of users and certain activities). It is important that the user should receive new recommendations, which would not be repeated with already completed ones or with low ratings ones.

Then the results are formed in the form of a recommendation and sent by the system to the user. The user can provide an evaluation of the recommendation in explicit or implicit forms. After receiving the assessment, the system must process it, update the user data and take into account the obtained results when making future recommendations.

2.6. Means for the system prototype implementation

The programming languages Java, JavaScript, and the React Native framework were chosen for the implementation of the mobile application prototype. The MySQL database management system was chosen to work with the database.

The system is based on the REST API architectural approach to perform CRUD (Create, Read, Update, Delete) operations and launch rule mechanisms, which will be used to select and perform operations on user data sets. One of the key benefits of REST APIs is that they provide a high level of flexibility. Data is not bound to resources or methods, so REST can handle multiple call types, return different data formats, and even change structure with the right hypermedia implementation.

3. Analysis of the obtained results

The main stages of the mobile application prototype work are as follows: user registration; viewing the recommendations catalogue for leisure activities; recommendations rejection; recommendation usage; viewing the achievements diary; recommendation completion; recommendation evaluation.

After loading the application, the user is greeted by the starter window of the application (Figure 6). It contains illustrations, welcome text, and buttons for entering the recommendation system or registration. The main meaning of the first page of the application is to provide the basic idea of its use, to offer authorization or registration for further use of the main functionality.

If the user has not yet created an account in the recommendation system, then he needs to go through the registration process. It consists of two steps:

- account creation;
- completion of the registration form.

The first step (Figure 6b) consists in entering the following data: Name (can be any nickname); Birthda; E-mail; Password. All fields are mandatory. Confirmation and proceeding to the next step also mean that the user has read and agrees to the rules of application usage. If all registration fields are filled, the user can proceed to the next step.

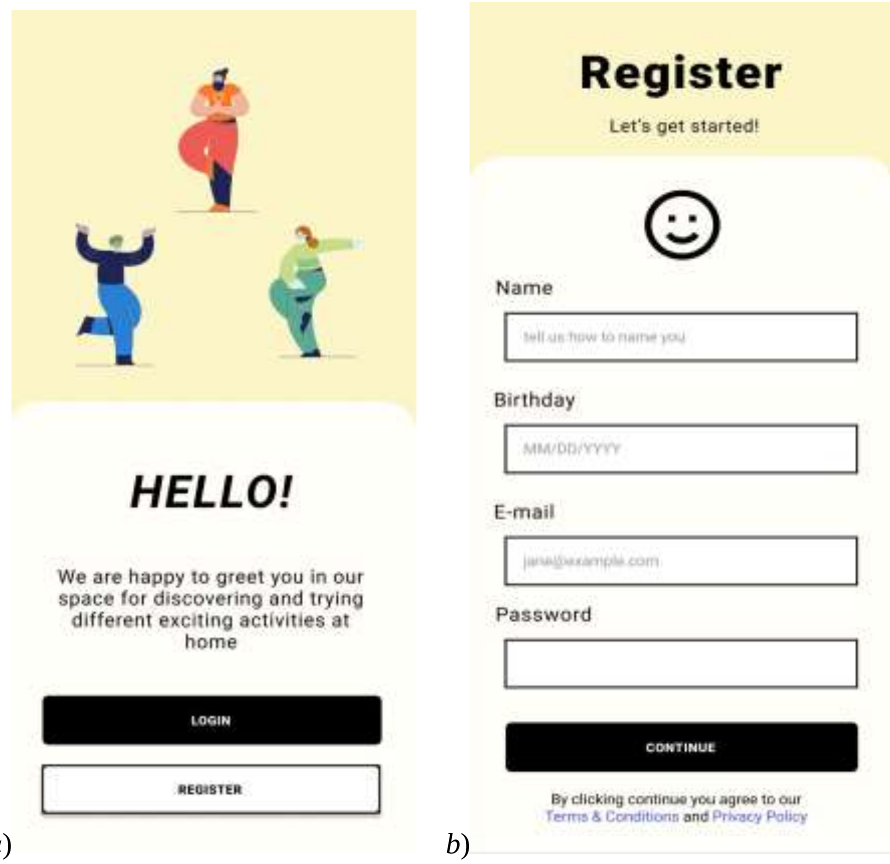
Before the start of the registration questionnaire with an initial set of questions, the answers to which will ensure the creation of an initial database of personal recommendations, an intermediate step of registration is added (Figure 7). Here, the user is provided with an explanation of the registration questionnaire. If the user is ready to answer the questions, he can proceed to the questionnaire. However, the user is also given the opportunity to skip the registration form and go straight to application usage. This is foreseen in order to provide a convenient user experience.

After the user chooses to proceed to the registration questionnaire, the system will open the first selected question from the database (Figure 8). Different questions are generated for different users (Figure 9). Next, users will take short surveys when asked to generate personalized recommendations.

To answer a question, the user needs to click on the proposed answer options in the questionnaire. In order for the user to monitor the progress of completing the questionnaire, a question counter was added to the system in the format "*the number of given answers / total number of questions*". The user also has the option to skip the questionnaire at any step. If three or fewer answers are done, this means to the system that the user has not provided any answers at all. This amount is not enough to generate personalized recommendations, the database will be empty for the user, and he will only be able to browse and select popular recommendations.

As soon as the user completes the questionnaire, the registration stage is considered completed.

The application consists of pages such as "*Personal Recommendations*", "*Diary of Achievements*" and "*Profile Settings*".



a) *b*)

Figure 6: a) the first window of the application with options to enter the system or register; b) creation of a new user profile

Figure 7: Transition to the registration questionnaire

Figure 8: The first question of the registration questionnaire

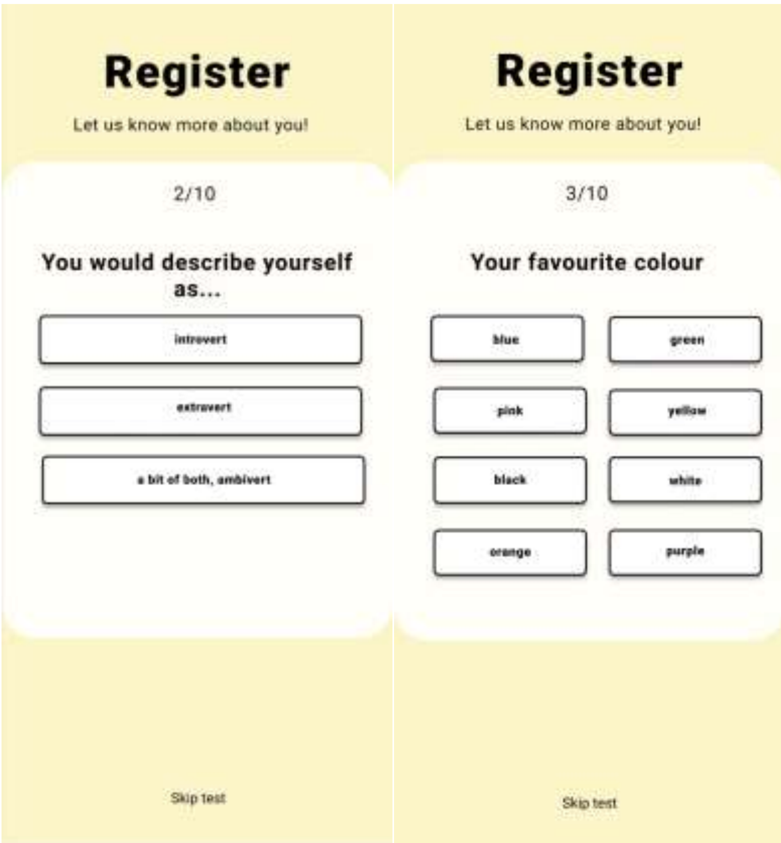


Figure 9: Registration questionnaire

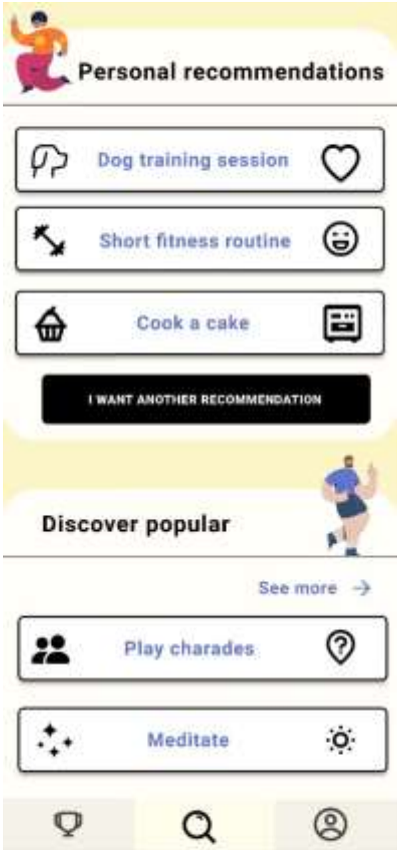


Figure 10: Page with personal recommendations

The “*Personal Recommendations*” page is considered the home page (Figure 10). On the page, the user can view a list of personal recommendations, as well as several popular items with the option to go to the full list. The page is divided into two sections. In the personal recommendations section, the user can choose one of the activities or send a request to generate a recommendation.

An important condition is that the generated recommendation should not repeat the positions of already provided personal recommendations contained in the list. The user can choose one of the recommendations and go to its description (Figure 11). The “Personal Recommendations” page contains its category, description, and rating formed by users. The user has the option to reject the recommendation (Figure 12) or start implementing it. If the user rejects the recommendation, the system considers it a negative rating. As well as positive evaluations, it is taken into account when providing future recommendations. Offers that are considered similar to the rejected offer will be rejected by the system and will not be offered to the user.

After the user begins to implement the recommendation for leisure activities, it will appear in the diary (Figure 13).

If there is an active recommendation, the diary is divided into two sections, which correspond to the current implementation of the recommendation and those that have already been completed. In the case of a newly created user profile, the list of completed recommendations is empty. Upon completion of the recommendation, the user must leave a rating (Figure 14).

This is a mandatory step that cannot be skipped. Thus, evaluations are collected for recommendations, which are taken into account when proposing future leisure time-management. Scores are saved and displayed to the user. The given rating of the recommendation affects its overall rating. After each evaluation, the recommendation can rise higher in the popular recommendations list, conversely, fall several positions lower. When the user gives a rating after completing the recommendation, it goes into the history of the diary of achievements (Figure 15).

In this case, the list of started recommendations is hidden. A combination of several recommendations is allowed, and it does not matter if this activity is short- or long-term.

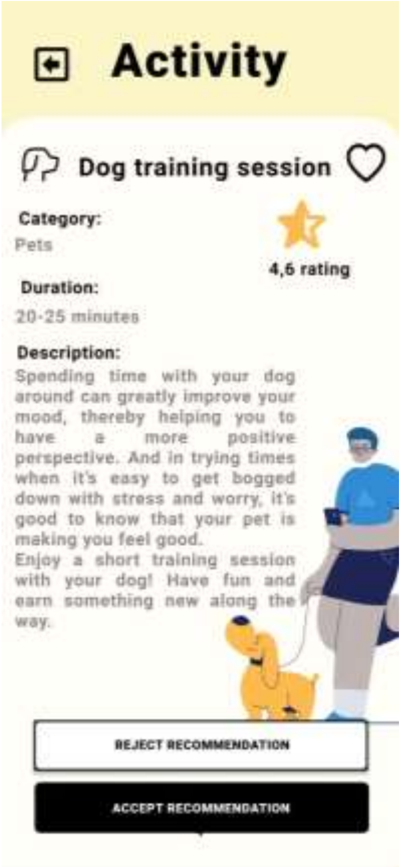


Figure 11: Page with recommendation description; c) page with recommendation rejection

Figure 12: Page with recommendation rejection

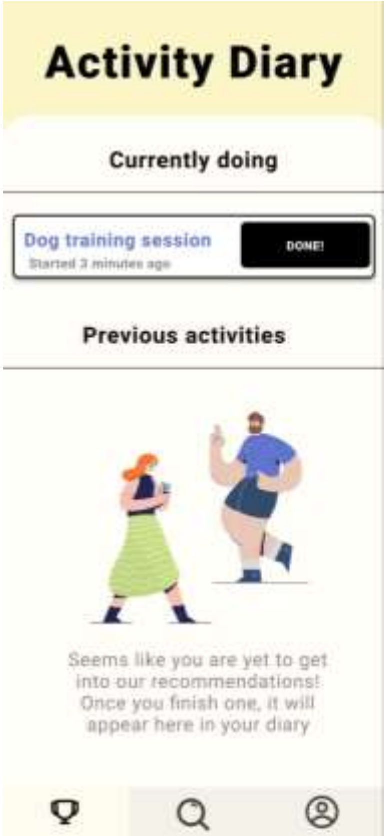


Figure 13: Page of the user's diary of achievements

b) 

Figure 14: Completion of the recommendation

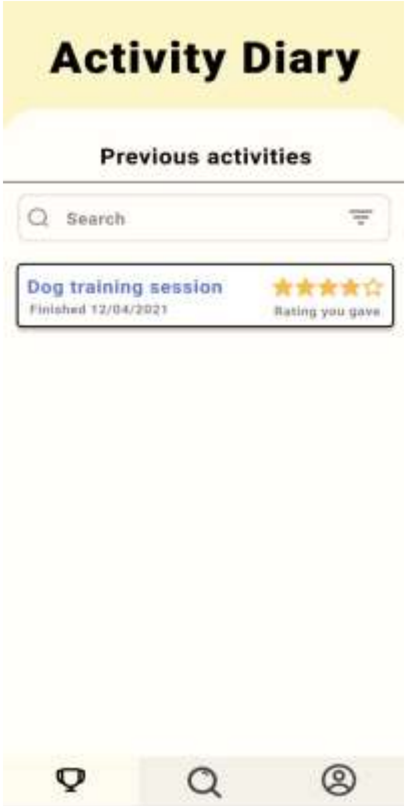


Figure 15: Diary of achievements with completed activity

4. Conclusions

The recommendation system is aimed at reducing the negative effects on the psycho-emotional state of a person who is in forced quarantine. Unlike other recommendation systems for spending leisure time at home, which offer only passive types of activities (for example, watching movies, or series), the recommendations of the developed prototype are also active, of course, taking into account the characteristics of each user. The result of the application of the recommendation system for leisure time-management in quarantine conditions is:

- reducing the level of anxiety and excitement that builds up in connection with staying at home in situations of uncertainty - the use of building a user's psychological portrait makes it possible to better understand not only a person's interests and hobbies, but also his temperament, level of activity, and behavioral characteristics;
- increasing the level of self-satisfaction as a result of the recommendations implementation and the "human face" of the system – an important aspect is the display for the user of the activities progress, keeping a diary of achievements, and the presence of encouragement in the form of feedback support and a reward accumulation system;
- promoting the process of learning new habits and knowledge – the base of the offered activities variety will help users not only to fill their free time at home but also to discover new interesting activities. When recommending activities, the system takes into account a certain logical sequence that will enable the user to develop his abilities;
- improving the level of physical and mental health – thanks to the implementation of relevant recommendations that have a positive effect on a person's well-being, there will be a stabilization or increase in the level of a person's mental and, at the same time, physical health. Which is quite an important factor during the quarantine conditions;
- economic effect – in addition to the fact that the recommended activities are limited to the home, for their implementation, it will be enough to use household means, without attracting additional resources.

The usage of the developed recommendation system is not limited to quarantine. Its services will be useful for people with disabilities that have led to temporary immobility. The specification of such features will need to be obtained directly from the user during surveys.

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