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Practical Approach to Designing and Implementing a Recommendation System for Healthy Challenges

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Abstract: Background: The COVID-19 pandemic has worsened sedentary lifestyles and unhealthy eating habits. It is crucial to promote proper training and healthy habits for all to prevent physical and cognitive decline. This should be a priority in health and education initiatives to reduce deaths and noncommunicable diseases. Guidelines for nutrition, physical activity, and sleep emphasize the importance of healthy habits. The goal is to develop a recommendation tool with a diverse range of challenges to positively impact users' health. Methods: The process involves thoroughly obtaining precise user profiles through widely used questionnaires such as the Short-Form Health survey, the short Healthy Eating Index, and the Oviedo Sleep Questionnaire, and characterizing the challenges. Then, an algorithm will be developed to identify and prioritize the most suitable challenges for each user, ensuring personalized recommendations. Results: A pool of 30 health challenges was created based on reputable recommendations and experts. The system underwent validation by external experts and received positive user feedback, confirming its effectiveness. The panel of experts and users validated the personalized and reliable recommendations. Conclusions: Simple lifestyle interventions have shown promise for primary prevention in developed countries. A prototype system has been created to evaluate the individual weakness of users and suggest evidence-based lifestyle challenges. The system conducts a thorough health assessment and ensures feasibility for preventive purposes. Validation has proven the system's effectiveness in recommending health-enhancing challenges with no adverse effects. The design of the model supports the seamless addition of new challenges by eventual third parties, ensuring interoperability and scalability.

Keywords: challenge; health promotion; healthy habits; physical activity; recommender algorithm; healthy lifestyle

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1. Introduction

Nowadays, one of the major issues in the developed world is the prevalence of sedentary lifestyles [1–5] and inadequate eating habits [6–9], both of which were accentuated by the recent COVID-19 pandemic and remain inadequate after the pandemic. After the conclusion of the aforementioned pandemic, and to state the redundancy, sedentary behavior and poor dietary and behavioral habits have come to be considered as the public health pandemic of the 21st century, with their corresponding economic cost [5]. To be more specific, the economic cost arising from physical inactivity currently stands at around \$67.5 billion worldwide [5], and the World Health Organization (WHO) estimates that it will continue to increase by \$27 billion annually, reaching an estimated annual expenditure of \$300 billion due to physical inactivity by the year 2030 [10]. "The economic burden of physical inactivity is significant and the cost of treating new cases of preventable non-communicable diseases (NCDs) will reach nearly US\$ 300 billion by 2030", the WHO states [10].

Considering the general increase in life expectancy worldwide (according to the WHO, it has grown by five years since the year 2000 [11]), it becomes evident that promoting proper training and adopting healthy lifestyle habits among all segments of the population is crucial for preventing physical and cognitive decline. Inculcating these habits should be a primary objective of health and education initiatives in the present era.

From the perspective of primary prevention, defined by Caplan [12] as "the measures taken to prevent the occurrence of a disease", or by the WHO [13] as "measures aimed at avoiding the occurrence of a disease or health problem by controlling causal and predisposing factors", it is reasonable to assert that a significant number of deaths and illnesses can be prevented by adopting a healthy lifestyle [14–16]. Unhealthy dietary habits and physical inactivity significantly increase the risk of developing NCDs [17,18]. NCDs account for 74% of global annual deaths, making up seven of the top ten causes of death worldwide [19]. As such, promoting healthy lifestyle habits, encompassing nutrition, physical activity (PA), and mental well-being, is a matter of paramount importance for countries in the Organization for Economic Cooperation and Development (OECD). Low adherence to nutritional, PA, and behavioral plans remains a significant obstacle to establishing these habits.

In these domains, which encompass healthy lifestyle habits including nutrition, PA, mental health, and sleep quality, well-established guidelines exist. These guidelines include healthy eating guidelines (HEG) from organizations such as the Food and Agriculture Organization (FAO) [20], US Department of Health and Human Services [21], and the WHO [18,22,23]. Additionally, there are guidelines on PA practice and its benefits for physical and mental health supported by research [14,15]. Furthermore, the National Sleep Foundation (NSF) provides sleeping guidelines (SG) [24,25].

In the current literature, various proposals can be found aimed at promoting these mentioned healthy habits. Examples of such initiatives include Public GYM [26], PRECIOUS (PREventive Care Infrastructure Based On Ubiquitous Sensing) [27], Fit brains trainer [28], Sworkit Lite [29], SAFER (Smart Assistance Platform for EldeRly Care) [30], HyperRecSysPA (PA Recommender System for Patients With Arterial Hypertension) [31], Mind Match [32], and Mindcraft [33].

These proposals can be classified into three groups according to the domain of human health they affect, pertaining to PA, mental health and nutrition.

In the first group, among the proposals related to the practice of PA, we have Public GYM [26], which is a mobile recommender system (hereafter RS) that employs artificial intelligence techniques to offer personalized exercise routines to users, specifically targeting PA in public outdoor gyms. The system takes into consideration the user's anthropometric characteristics and specific medical conditions. For example, a diabetic user would receive customized strengthening exercises that avoid targeting areas where insulin is typically administered. Another proposal is PRECIOUS [27], an Android application developed to promote a healthier lifestyle. This application analyzes various factors such as diet, PA, stress levels, sleep patterns, and environmental conditions to evaluate the user's current health status. Based on this analysis, the application suggests activities that can contribute to enhancing overall well-being. The recommended activities are tailored to combat type 2 diabetes and cardiovascular diseases. Sworkit Lite [29] is a fitness application focused on physical strengthening. It offers a range of routines including strength exercises, cardio workouts, stretching, and yoga. Users can select the specific body area they wish to exercise, and the system provides a set of routines along with recommended durations for optimal results. Lastly, HyperRecSysPA [31] is a PA RS specifically designed for hypertensive patients. The system collects relevant information from hypertensive individuals to provide personalized recommendations for PA based on their specific needs and conditions.

In the second group, regarding mental health, we encounter Fit brains trainer [28], which is an application designed to enhance the cognitive capacity of older adults. The application presents users with memory-testing games that progressively increase in difficulty as they successfully complete each level. The system continuously monitors and analyzes the user's progress, and based on their performance, suggests new games that align with their capabilities. SAFER [30] is an RS that focuses on recommending recreational and cultural events for seniors. Its objective is to suggest cultural activities based on the user's preferences and the availability of events in the city. Mind Match [32] aims to promote mental health among adolescents to help them develop healthy habits and coping mechanisms for the future. Mind Match incorporates mental health education into the high school curriculum to ensure every student accesses the resources needed to understand their mental health. And finally, Mindcraft [33], is a mobile mental health platform for children and young people, which integrates passive sensor data monitoring with active self-reported updates through an engaging user interface to monitor users' well-being.

In the third group, regarding healthy eating, we came across the research conducted by Bundaksa et al. [34], in which they developed a food recommendation system tailored for the elderly population. Drawing upon behavioral characteristic data, the system generates various clusters to provide dietary recommendations to each of them. Another study focused on healthy nutrition is that of Namgung et al. [35], in which they employed smart plates to assess the eating habits of young children. They weighed the plate before and after each meal to calculate the amount of food consumed by the child. Using these data, they computed the quality of macronutrient intake among the children to establish groups based on their deficiencies and provide more appropriate dietary recommendations.

All these studies aim to improve people's health by addressing the specific characteristics of individuals, focusing on specific and limited areas.

The present work is situated within the context of promoting a comprehensive and holistic improvement in people's health. It considers the physical, mental, nutritional, and sleep habits of individuals, based on their unique characteristics, needs, and particularities. This is achieved through the adoption of healthy habits and the promotion of adherence to these habits using gamification techniques.

Previously published studies have demonstrated that gamification has been successful in enhancing engagement in physical activity through elements such as challenges, goal setting, scoreboards, or rewards, as indicated in these two systematic reviews [36,37]. From the perspective of mental health, relevant research has explored how gamification contributes to increased user adherence, as exemplified by studies focused on applications like Mindcraft [33]. Conversely, the findings from these two systematic reviews [38,39] suggest that no significant differences exist between outcomes derived from apps featuring gamification elements and those lacking them. In the realm of healthy eating, the systematic review conducted by Alghamdi et al. [40] highlights that the utilization of gamification elements effectively facilitates imparting nutritional knowledge and combating children obesity. Finally, regarding sleep habits, the utilization of gamification techniques such as goal-based gamification, continuous feedback, and social support has shown promise in positively influencing individuals' sleep patterns, as stated in [41,42].

The gamification environment proposed involves the presentation of proper activity plans in the form of challenges. As presented in a previous paper by the authors [43], participants are encouraged to achieve the goal within each challenge through the incentive of prizes and receiving daily progress updates on their mobile devices, indicating their progress in the subscribed challenges and whether they are progressing adequately or need to improve their performance.

Within this framework, the personalized and accurate selection of challenges for each specific user holds special relevance. Therefore, automated support is sought to assist in the selection and suggestion of such challenges to the general population. In this context, the proposed challenges provide concrete and measurable indications for physical, mental, nutritional, and sleep activities, defined in terms of frequency and duration, aimed at promoting holistic improvement in people's health according to their needs and characteristics.

Considering the above, this work aims to create a model for recommending challenges that positively impact the health of participants. The model includes characterizing the user, challenges, and an algorithm for generating appropriate suggestions tailored to each user's specific profile. The model must be specific, formal, and validated, as demonstrated in this paper. This work targets individuals without medical conditions and considers physical, mental, and nutritional aspects.

2. Materials and Methods

The objective is to make suitable and adequate recommendations of challenges that may create a positive impact on the life of the citizens and with potential to become habits in their daily lives. These challenges will be selected from an extensible pool provided also in the frame of this work. To create such a recommendation tool, a series of previous processes will be required.

Firstly, precise characterizations of users and their health-related needs will be obtained through widely used questionnaires. The Short-Form Health Survey (SF-36) in its Spanish version [44], the Short Healthy Eating Index (sHEI-15) adapted for the Spanish population [45], and the Oviedo Sleep Questionnaire (OSC) [46,47] will be utilized. In this work, the SF-36 questionnaire provides scores for six dimensions related to individuals' physical and mental health. As it is well known, the summatory components of the SF-36 are the Physical Component Summary (PCS) and Mental Component Summary (MCS). Since these were overarching assessments, we opted to utilize the specific subscores outlined in Section 2.1 (User Profile). By doing so, we were able to differentiate between the most suitable challenges using the mentioned subscores to make a more suitable recommendation. The sHEI-15 yields six dimensions pertaining to eating habits, while the OSC measures three dimensions related to sleep quality. These questionnaires are essential for accurately defining user profiles. Additionally, it is necessary to thoroughly characterize the challenges. Finally, an algorithm will be developed to identify and prioritize the most suitable challenges for each user.

2.1. User Profile

In order to provide personalized challenge suggestions, it is important to accurately describe the user. To achieve this, users are required to answer a series of questions divided into two sections. Firstly, there are final questions aimed at capturing the user's basic biophysical data, sociodemographic background, and physical condition.

Following that, users are presented with the Spanish versions of the SF-36, sHEI-15, and OSC questionnaires. These questionnaires, previously validated and widely accepted in the field of health, allow for a more precise characterization across various dimensions.

There are nine items included in this biophysical and sociodemographic characterization, which are listed below and can be found in greater detail in Table 1.

- Age group. In this section, users are required to enter their age range, categorizing them into specific age groups, following the WHO classification [15], such as: children and adolescents (5–17 years), adults (18–64 years), or older adults (65 years or more).
- Gender. Users need to select their gender, choosing either male or female.
- Weight. Users are asked to provide their weight to calculate their BMI and determine the appropriate BMI range.
- Height. Users are asked to provide their height to calculate their BMI and determine the appropriate BMI range.
- Special groups. Users must indicate if they belong to any special groups using the WHO's categorization [48]. This includes groups such as those with skin diseases, pregnant or postpartum individuals, individuals with sleep or wakefulness disorders, individuals with endocrine diseases (e.g., diabetes), individuals with circulatory system diseases (e.g., hypertension), or individuals with musculoskeletal or connective tissue diseases (e.g., arthropathies, chondropathies).
- Injuries. Users should specify if they have any temporary injuries that are not covered in the "Special Groups" section. They need to indicate whether it is an upper body, lower body, or trunk injury.
- Daily time available. Users are asked to indicate the amount of time they have available each day for training.

- Material available. Users need to specify the materials they have access to for their training.
- Available spots. Users should indicate if they have the option to perform their training in different locations.

Table 1. Description of the items used for the complete characterization of the user profile.

Source of Information	Item	Set of Possible Values
User-entered	Age group	5–17 years. 18–64 years. 65 years or more.
	Gender	Male. Female.
	BMI	By means of the weight and height of the users, the BMI is calculated to classify them in the corresponding group. BMI < 18.5 = underweight. 18.5–24.9 = normal weight. 25–29.9 = preobesity. 30–34.9 = class I obesity. 35–39.9 = class II obesity. >40 = class III obesity.
	Special groups	Skin diseases. Pregnancy, childbirth, or puerperium. Sleep or wakefulness disorders. Endocrine diseases (e.g., diabetes). Diseases of the circulatory system (e.g., hypertension). Diseases of the musculoskeletal system or connective tissue (e.g., arthropathies, chondropathies). None.
	Injuries	Upper body. Lower body. Trunk. None.
	Daily time available	<15′. Between 15′ and 30′. >30′.
	Available spots	Pool. Sea. Country or city. Indoor house. Gym.
	Required material	Bicycle. Barbells. Sliding discs. Jumping rope. No material. Others.
SF-36	PF	Rating for the physical function dimension (0–10)
	BP	Rating for the bodily pain dimension (0–10)
	GH	Rating for the general health dimension (0–10)
	V	Rating for the vitality dimension (0–10)
	SF	Rating for the social function dimension (0–10)
	MH	Rating for the mental health dimension (0–10)
sHEI-15	FC	Rating for the fruit consumption dimension (0–10)
	LVC	Rating for the legume and vegetable consumption dimension (0–10)
	GVC	Rating for the green vegetable consumption dimension (0–10)
	ASC	Rating for the dimension of consumption of added sugars (0–10)
	WGC	Rating for the whole grains consumption dimension (0–10)
	DC	Rating for the dairy consumption dimension (0–10)
OSC	SSS	Rating for the subjective sleep satisfaction dimension (0–10)
	IS	Rating for the insomnia dimension (0–10)
	HS	Rating for the hypersomnia dimension (0–10)
Acceptable Effort	AE	Obtained through the arithmetic mean of the PF and MH components.

BMI: Body mass index; PF: Physical function; BP: Bodily pain; GH: General health; V: Vitality; SF: Social function; MH: Mental health; FC: Fruit consumption; LVC: Legume and vegetable consumption; ASC: Added sugar consumption; WGC: Whole grains consumption; DC: Dairy consumption; GVC: Green vegetable consumption; SSS: Subjective sleep satisfaction; IS: Insomnia; HS: Hypersomnia: AE: Acceptable effort.

In the second set of questions, the user is presented with questionnaires aimed at establishing their user profile. This is completed by evaluating 15 pertinent aspects of the user's condition, which include:

- Six evaluations from the SF-36 questionnaire, which assess the user's physical and emotional well-being. These evaluations cover physical function (PF), bodily pain (BP), general health (GH), vitality (V), social function (SF), and mental health (MH).
- Six evaluations from the sHEI-15 questionnaire, focusing on the user's eating habits. These evaluations encompass fruit consumption (FC), legume and vegetable consumption (LVC), green vegetable consumption (GVC), added sugar consumption (ASC), whole grain consumption (WGC), and dairy consumption (DC).
- Three evaluations from the OSC questionnaire, targeting sleep quality. These evaluations include subjective sleep satisfaction (SSS), insomnia (IS), and hypersomnia (HS).

Consequently, each user is characterized by a total of 24 features, as illustrated in Table 1. Nine of these features are provided directly by the user, resulting in eight values (weight and height together form the BMI item). Additionally, there are six dimensions from the SF-36 questionnaire, six dimensions from the sHEI-15 questionnaire, three dimensions from the OSC questionnaire and lastly the Acceptable Effort (AE).

In addition to the previous characterization obtained from the users' responses to a set of questionnaires and question batteries, another parameter named Acceptable Effort (AE) is proposed. This parameter is used in the algorithm to model the physical and mental capacities of each particular user. Its definition is based on the Royal Spanish Academy and refers to the "energetic utilization of physical strength against an impulse or resistance" or the "energetic utilization of vigor or activity of the spirit to overcome difficulties" [49]. Furthermore, Nicholls [50] equates the concept of effort with ability and stipulates that it is influenced by the physical and emotional capacities of individuals. In our specific context, the concept of AE is defined as an individual's ability to confront a specific challenge, taking into account both physical and psychological aspects.

2.2. Challenges Characterization

In order to make well-informed decisions, it is essential to thoroughly characterize each challenge and assess its relevance in relation to the user's specific dimensions. By conducting a meticulous analysis of pertinent factors, a model comprising 24 features, based on expert consensus, was developed to represent these challenges. These data align with the established user characterization in terms of features and dimensions.

These values will play a critical role in the challenge selection process as elaborated upon in a two-step approach.

Initially, we will utilize eight of these features to eliminate challenges that are evidently incompatible, such as not being within the appropriate age group or having incompatible medical conditions. Secondly, up to 16 other features will be employed to assess the suitability of the challenge for the user being evaluated. The former ones correspond to the same items used for the bio-physical and sociodemographic characterization of the users. For each one of them, response options will be provided to properly characterize each challenge in relation to the user's characterization.

The latter features or dimensions, up to 16, introduced in the model to find out the most suitable challenge are associated with how beneficial the challenge is for each of the dimensions assessed by the SF-36, sHEI-15 and OSC questionnaires. These pieces of data are completed with an estimate of the difficulty of the challenge by means of an item called Effort Required (ER) assessed by the mentioned experts. Table 2 shows a schematic of the items that allow characterizing a challenge and the possible response values for each one.

Table 2. Description of the items used for the characterization of each challenge.

Feature/Dimension	Set of Possible Values
Age group	5–17 years. 18–64 years. 65 years or more.
BMI excluded	BMI < 18.5 = underweight. 18.5–24.9 = normal weight. 25–29.9 = preobesity. 30–34.9 = class I obesity. 35–39.9 = class II obesity. >40 = class III obesity (World Health Organization, 2010).
Special groups excluded	Skin diseases. Pregnancy, childbirth, or puerperium. Sleep or wakefulness disorders. Endocrine diseases (e.g., diabetes). Diseases of the circulatory system (e.g., hypertension). Diseases of the musculoskeletal system or connective tissue (e.g., arthropathies, chondropathies). None.
Incompatible Injuries	Upper body. Lower body. Trunk. None.
Daily time required	<15′. Between 15′ and 30′. >30′. Any.
Development place	Pool. Sea. Country or city. House. Gym. Any.
Required material	Bicycle. Barbells. Sliding discs. Jumping rope. No material.
PF	Rating for the physical function dimension (0–10)
BP	Rating for the bodily pain dimension (0–10)
GH	Rating for the general health dimension (0–10)
V	Rating for the vitality dimension (0–10)

Table 2. *Cont.*

Feature/Dimension	Set of Possible Values
SF	Rating for the social function dimension (0–10)
MH	Rating for the mental health dimension (0–10)
FC	Rating for the fruit consumption dimension (0–10)
LVC	Rating for the legume and vegetable consumption dimension (0–10)
WGC	Rating for the green vegetable consumption dimension (0–10)
ASC	Rating for the dimension of consumption of added sugars (0–10)
WGC	Rating for the whole grains consumption dimension (0–10)
DC	Rating for the dairy consumption dimension (0–10)
SSS	Rating for the subjective sleep satisfaction dimension (0–10)
IS	Rating for the challenge in the insomnia dimension (0–10)
HS	Rating for the challenge in the hypersomnia dimension (0–10)
ER	Rating for the effort required to carry out the challenge (0–10)

BMI: Body mass index; PF: Physical function; BP: Bodily pain; GH: General health; V: Vitality; SF: Social function; MH: Mental health; FC: Fruit consumption; LVC: Legume and vegetable consumption; ASC: Added sugar consumption; WGC: Whole grains consumption; DC: Dairy consumption; GVC: Green vegetable consumption; SSS: Subjective sleep satisfaction; IS: Insomnia; HS: Hypersomnia; ER: Effort required.

2.3. Recommendation Algorithm Design

After establishing the value for the different features or dimensions of each challenge according to the proposed model and assessing the user parameters, the recommendation algorithm can be defined. In this task, the model was implemented using Python, and it was supported on Google Colab.

The recommendation model proposed tries to mimic the rationale for the selection of a challenge for a healthy person by a human expert in terms of screening criteria. Going into detail, once the user has access to the system, there is a set of steps undertaken to receive the final recommendation that goes as follows:

1. Data gathering from the user.

The user is requested to answer some general questions about bio-physical and sociodemographic definition of the users and a set of well-known questionnaires (already discussed in previous sections). With the obtained responses, a detailed profile is generated that addresses all relevant dimensions of the user. This includes the physical dimension (based on PF, BP, and GH scores), psychological dimension (MH, V, and SF), fruit and vegetable consumption dimension (FC, GVC, and LVC), added sugars, whole grains, and dairy consumption dimension (ASC, WGC, and DC), and sleep dimension (SSS, IS, and HS). The overall score for the food dimensions is calculated as the arithmetic mean, while the other dimensions use the geometric mean. The geometric mean is applied instead of the arithmetic ones to prevent high values from hiding the relevance of low values in close features. The practical deployment of the model confirmed the positive practical impact of this approach.

Additionally, the previously mentioned AE index is calculated by taking the arithmetic mean of the PF and MH components. This index reflects the user's physical and mental capacity to undertake the challenges. Table 3 shows, as an example, the complete profile of an individual entered the RS, which is hereinafter referred to as tester A. This information is also depicted in Figure 1, where on the vertical axis, a dimensionless grading scale from 0 to 10 is observed; and on the horizontal axis, a list with the name of the 15 dimensions is assessed. The reader is presented with the comprehensive profile of an actual individual integrated within the system. This profile meticulously displays the achieved scores across the assessed dimensions. Within this model, higher scores indicate more favorable outcomes. It is noteworthy that the subject's lowest score is attributed to their consumption of whole grains. This indicates that this particular user has a deficiency in the consumption of whole grains, hence the low score obtained in this dimension. This applies to the other values as well: a low value indicates a poor level. This way, a low level of sugar consumption would imply that a lot of sugar is ingested.

Table 3. The complete profile of the tester A included in the RS.

Feature/Dimension	Provided Data
Age group	18–64 years.
Gender	Male.
BMI	18.5–24.9 = normal weight.
Special groups	Skin diseases.
Injuries	None.
Daily time available	>30′.
Possible spots	Pool. Sea. Country or city. Indoor house. Gym.
Material available	Bicycle. Barbells.
PF	9.5
BP	4.8
GH	8.7
V	8.0
SF	10.0
MH	6.4
FC	6.5
LVC	10.0
GVC	6.2
ASC	10.0
WGC	2.5
DC	4.2
SSS	5.0
IS	6.1
HS	8.3
AE	7.95

BMI: Body mass index; PF: Physical function; BP: Bodily pain; GH: General health; V: Vitality; SF: Social function; MH: Mental health; FC: Fruit consumption; LVC: Legume and vegetable consumption; ASC: Added sugar consumption; WGC: Whole grains consumption; DC: Dairy consumption; GVC: Green vegetable consumption; SSS: Subjective sleep satisfaction; IS: Insomnia; HS: Hypersomnia; ER: Effort required.

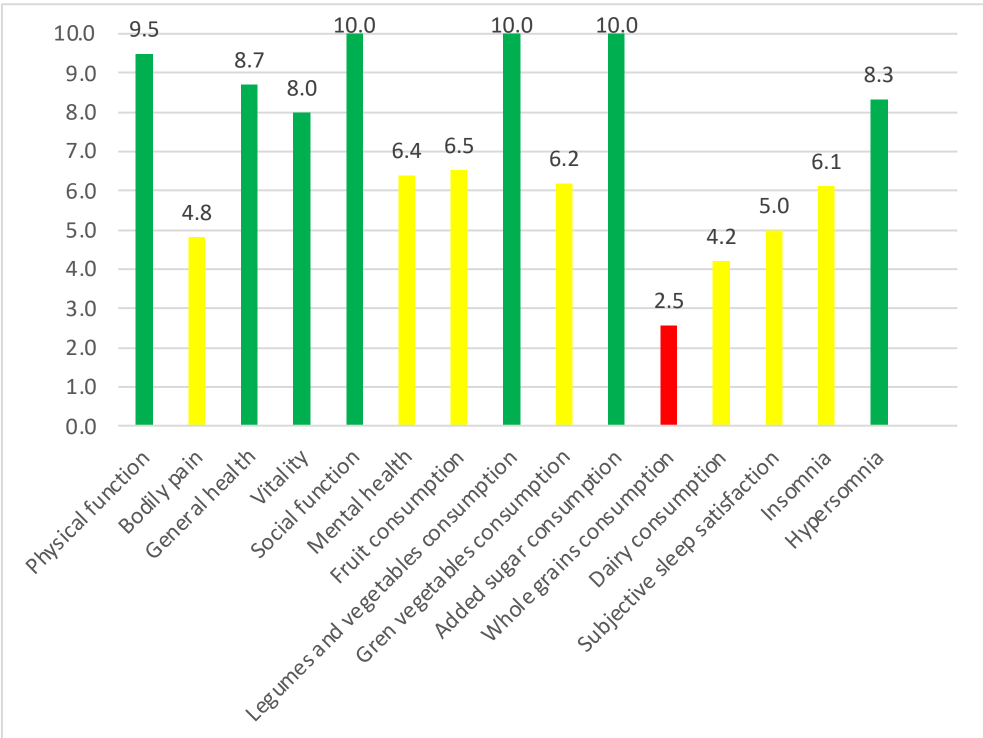


Figure 1. Profile of the tester A included in the RS. Colors highlight the dimension scores, from 0 to 3.33 are in red, from 3.34 to 6.66 are in yellow and from 6.67 to 10 are in green.

2. Filtering

Comparing the data of the user under consideration with each challenge in the pool, those challenges unsuitable for this particular user are excluded from the process. This decision is based on factors such as age group, incompatible BMI, belonging to ill-advised groups, time constraints, location incompatibility, and lack of necessary equipment. This filtering is based on explicit data gathered directly from the user profile.

Also, a second filtering step is performed. The algorithm compares the user's AE (estimated as previously mentioned) with the ER by each challenge according to the evaluations by experts. Challenges that exceed the user's AE level are eliminated from the recommendation process. A 10% increase in the ER is applied to ensure the inclusion of challenges in the limit of the user. For the user tester A described in Table 3, the following challenges shown in Supplementary Materials are not compatible:

- Challenge 8: this challenge is not compatible with skin diseases and the ER is higher than the tester A's AE. The AE of the tester A after the 10% increase goes up to 8.745.
- Challenge 13: the use of a jumping rope is necessary to perform that challenge.

3. Matching based on critical features

The model identifies the most deficient dimensions in users, aiming to improve their capabilities comprehensively. Challenges are recommended to address these weaknesses while considering the holistic nature of health. This approach aligns with the clinical consensus applied to non-professional sportsmen/sportswomen or the general population with no particular requirements (Figure 2a). According to this evaluation, a ranking is created to provide quantitative, not just qualitative, information about the best set of challenges for a given user. This is the most intensive phase in terms of computational power. As shown in Figure 2b, for each of the challenges remaining in the pool of possible recommendations, i.e., those that have not been filtered out, an evaluation process is launched (check Algorithm 1).

Algorithm 1. Pseudo-code for the evaluation of a certain challenge (referred to as currentChallenge) for a certain user (referred to as currentUser).

```
n -> 1; totalScore -> 0;
repeat while n <= 5; {
    //select the worst dimension of the user
      SearchWeakestFeature(currentUser) -> worstDimension;

          //evaluate the challenge under consideration regarding the previous dimension
       EvaluateRelevance(currentChallenge, worstDimension) -> partialScore;
    //update the total score adding the new partial
        totalScore -> totalScore + partialScore * Coef2 ^ (adapt ^ (n − 1))}

        //remove the current dimension from the user. So, on the next iteration,
        this dimension will not be considered
          RemoveDimension(currentUser, worstDimension);
                n -> n +1 ;
}
return totalScore
```

As the reader may note, the process is launched for each challenge in the context of each user. The result is a numeric evaluation of the considered challenge.

4. Ranking

Using the scores generated in the previous step, an ordered list of challenges is created (Table 4). Therefore, the system will not offer just a list of recommended challenges, but it will also offer quantitative information about how suitable each challenge is in relation to the others in a simple and intuitive way. For the user tester A, the most suitable challenge according to the presented model is challenge number 21, which is named "Eating whole grains"; see Supplementary Materials.

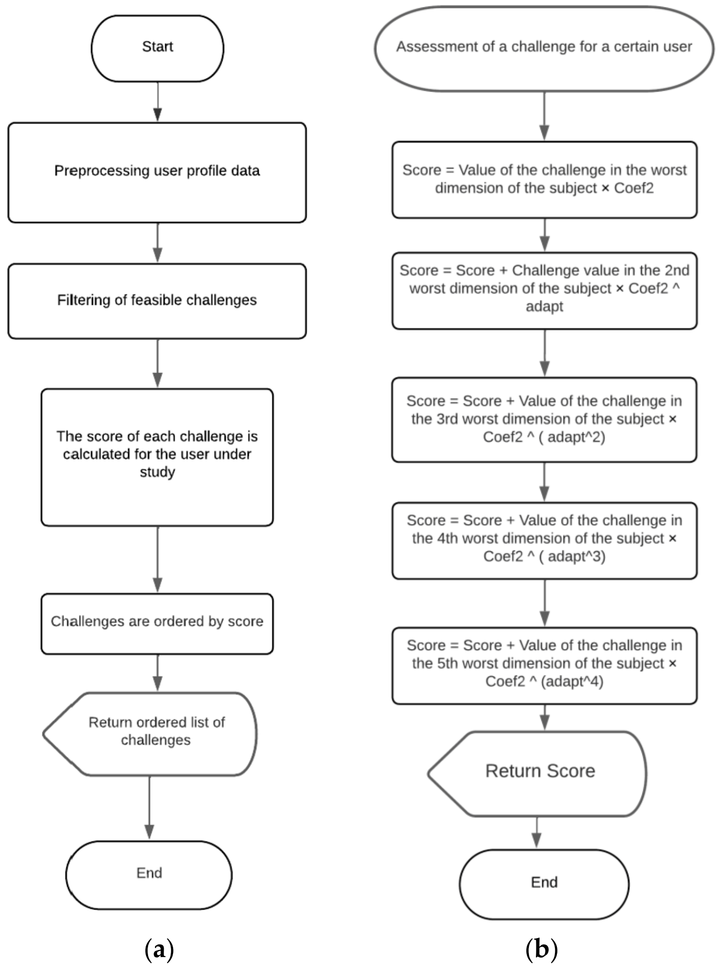


Figure 2. (**a**) Flowchart of the general operation of the recommendation algorithm; (**b**) Flowchart of the algorithm for calculating the score of each challenge for each user.

To ensure the desired adjustment of the recommendation algorithm and detect errors, an initial set of tests was launched in a laboratory context using synthetic data for testing the codification of the algorithm. Later on, a total of 30 user profiles from volunteers and 30 new validated challenges were introduced to validate the model and to ensure a proper order of recommended challenges for each user. Using these data and conducting tests with different values of Coef2 and adapting, a fine-tuning of the algorithm parameters was carried out to ensure that the algorithm operated as intended. In particular, these parameters are fixed values (0.25 and 0.5, respectively) that turned out to provide the best possible results on the existing data according to the experts' recommendations. As the reader may note, the final aim was to closely approximate expert recommendations when applied to actual user profiles and the pool of actual challenges.

Summing up all, the algorithm provides personalized recommendations that align with the user's capabilities and circumstances, as the model takes into account the features of each user in an independent manner.

Subsequently, in the validation section, it can be observed how actual challenges and profiles are used to confirm the algorithm's proper functioning.

Table 4. Ranking of the 30-challenge pool for the user tester A.

Challenge	Score
21	23.71
19	22.14
16	20.68
12	19.72
9	18.85
10	17.80
11	16.77
5	16.53
18	16.17
17	16.01
22	15.72
20	14.46
2	14.16
24	14.14
14	13.90
6	13.80
23	13.52
3	13.45
7	13.44
15	13.26
29	13.22
27	12.78
4	11.57
1	11.55
26	9.44
25	9.06
28	6.75
30	5.68
13	Excluded
8	Excluded

3. Results

A pool of 30 challenges was created to specifically positively impact the users' health. These challenges are defined according to a formal model. Therefore, the inclusion of new challenges turns out to be quite straightforward, allowing governmental agents or other stakeholders to instantiate new challenges to promote these healthy habits among the population just by following the present model. In the case of this study, the challenges were created using the support of scientific evidence collected in the literature of the domain and are aligned with the PAG for Americans [14,15], the guidelines provided by the WHO and the FAO [18,20–23], as well as the recommendations of the National Sleep Foundation [24,25].

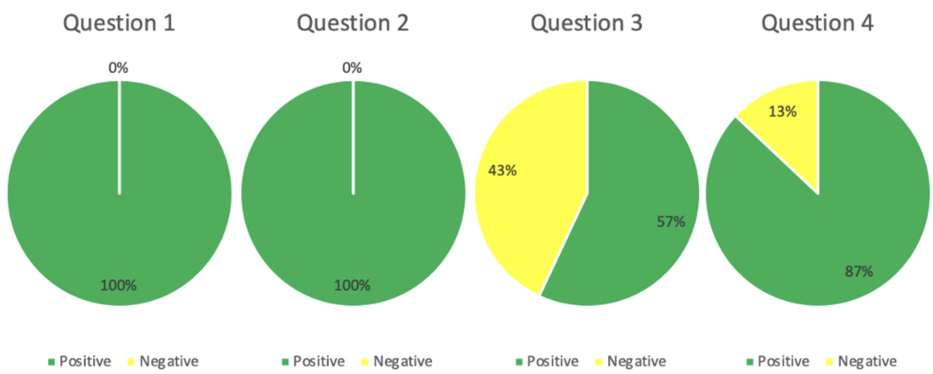
Additionally, a healthy diet is recommended, emphasizing the reduction in sugar consumption to less than 10% of total daily calorie intake, limiting fat intake to less than 30%, and restricting daily salt intake to less than 5 g. It is also advised to minimize the consumption of processed foods, saturated fats (less than 10% of total calorie intake), and trans fats (less than 1% of intake). On the one hand, these dietary restrictions, applied in the general population, without particular pathologies, could reduce the risk of suffering from NCDs such as heart disease (such as myocardial infarction and stroke, often associated with hypertension), diabetes, and some types of cancer. This would improve people's quality of life and could prevent death in certain cases. Conversely, the consumption of fruits, vegetables, legumes, nuts, and whole grains is encouraged. A minimum of five servings of fruits and vegetables per day is recommended [17,18,20,22,23,51,52]. On the other hand, as indicated by the WHO and FAO, eating at least 400 g, or five servings of fruits and vegetables per day reduces the risk of developing NCDs and helps ensure sufficient daily intake of dietary fiber [20,23]. According to these evidence-based recommendations, the duration and frequency of each challenge were determined based on the specific type of activity being carried out.

Each challenge was evaluated to determine its potential benefits according to the proposed user profile dimensions. The values assigned to these dimensions signify the potential contributions within their respective domains, and they are established through the consensus of experts. These assessments hold paramount importance within the context of the recommendation process, as they establish the foundational framework for assessing the efficacy of each challenge with respect to the unique profiles of individual users.

As a result of the aforementioned, the reader can check in Supplementary Materials the pool of 30 challenges, including the scoring of each dimension. For each challenge, we specified which guides were used as a reference to determine the activities to be performed. We considered the recommended weekly time, the age group, and groups for whom it may be contraindicated.

The presented RS was tested using a data pool consisting of both users and challenges. The user pool comprised profiles of 30 individuals (18 men and 12 women) obtained through the previously mentioned questionnaires. The challenges in the system were evaluated by a panel of experts, including physicians, psychologists, nutritionists, and PA professionals. Using these data and the described model, the RS was launched, and recommendations were generated automatically.

The recommendations made by the RS underwent a dual validation process. Firstly, the approach presented in Ferretto et al. [31] was applied. Six external experts assessed the suitability of the top ten recommended challenges for each user. The multidisciplinary expert team evaluated the subjects who were presented with the ten most recommended challenges. In Figure 3, it is evident that experts responded positively in every single case to question 1. This indicates that none of the proposed challenges are considered harmful or counterproductive for the user; this positive unanimity is the result of the filtering phase of the algorithm, which does not allow an undesirable challenge to enter the user's recommendation. Similarly, in question 2, we obtained a 100% positive response rate, indicating that all the proposed recommendations have the support of the experts; again, because no challenge not compatible with the user can enter the recommendation, all the experts supported the proposed recommendation. Moving on to question 3, the positive and negative responses align with the changes that experts would suggest improving the recommendation.



Question 1:	"Could the challenges presented be counterproductive for the user and, therefore, would you advise against them?"
Question 2:	"Would the suggestions presented have your support in terms of recommendation?"
Question 3:	"Would you make any changes to the recommendation on the set of challenges presented?"
Question 4:	"If you consider that any challenge would not be necessary or advisable, please indicate which one(s)"

Figure 3. Distribution of experts' responses regarding the proposed personalized recommendation.

During this phase, intentionally adding unnecessary challenges for users resulted in a 43% occurrence of negative responses. Importantly, this trend aligns with cases where unnecessary challenges were purposely introduced, achieving an 87% correlation rate. This suggests that the existence of 87% of these contrived challenges, introduced to counteract expert bias, was indeed recognized.

For example, if a user attained a rating of ten points in the ASC metric, it would not be necessary for that user to be presented with a challenge aimed at improving their ASC within their recommended activities. However, if such a challenge was deliberately included for the user, experts should be capable of identifying it. As an illustration, consider the profile of tester A shown in Figure 1, where the challenge "Forget about sugar" would not be needed since tester A already achieved a perfect score of 10 in the ASC dimension.

It is worth noting that the 13% of fake challenges that went unnoticed can be attributed to the fact that these challenges were not considered problematic in any scenario. Instead, they were simply unnecessary and sometimes difficult to spot.

To ensure the validity of the recommendations, an extra validation strategy was applied. Additionally, the 30 initial users received their characterization according to the presented model and the ranked set of recommended challenges tailored for their particular profile. A brief survey consisting of three questions was also submitted to validate the proposal. This outcome is presented in Figure 4. Most users find the challenges achievable and feel confident about successfully finishing them. However, almost half of the users view the challenges as overly tough. This could be due to the inclusion of an additional 10% effort in the model. While this choice could be changed, the authors firmly believe that pushing users beyond their comfort zone can yield significant benefits.

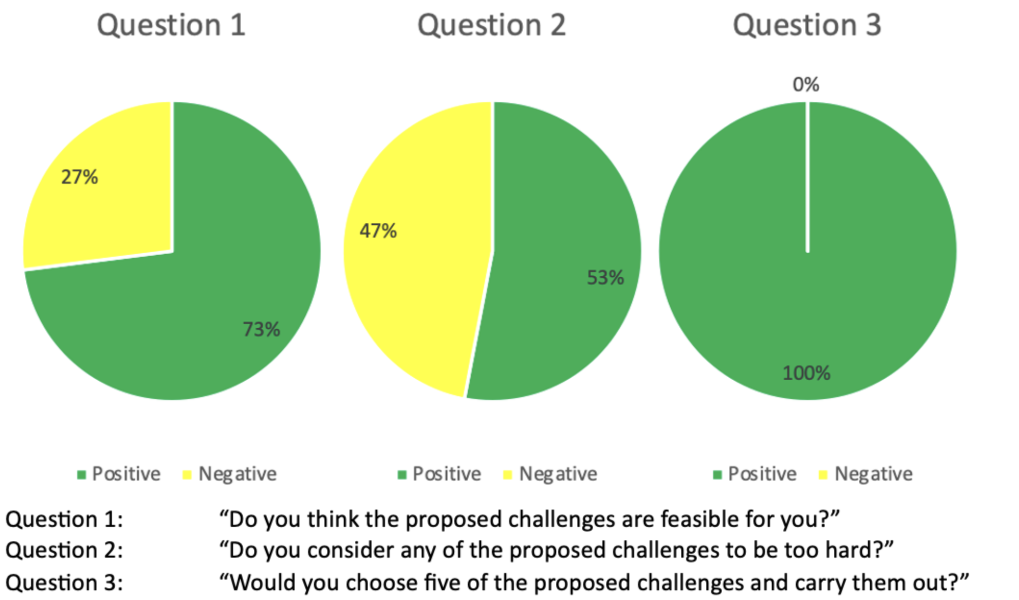


Figure 4. Distribution of user responses regarding the proposed personalized recommendation.

4. Discussion

A challenge recommendation tool was successfully developed, tested, and validated to meet the objectives of promoting healthy lifestyle habits among the general population. The tool considers individual characteristics and specificities, using methods and information based on scientific evidence.

When deployed in actual scenarios, this tool proves the capacity to reveal latent deficiencies covering diverse features that an individual might not be aware of. Furthermore, it automatically proposes challenges that should yield positive influences on their life. For instance, an individual could become aware that their poor sleep quality holds noteworthy implications for their health along with receiving a way for improving.

As highlighted in the introduction and underscored by the WHO, issues derived from physical inactivity and the accompanying burden of NCDs constitute a relevant issue in the so-called developed societies. Therefore, the successful integration of healthy habits within the population stands to potentially bring about a noteworthy improvement and prevention of health-related issues.

4.1. Comparison with Prior Work

As mentioned in the introduction, several existing approaches in the literature aim to promote healthy habits, such as Public GYM [26], PRECIOUS [27], Fit brains trainer [28], Sworkit Lite [29], SAFER [30], HyperRecSysPA [31], Mind Match [32], Mindcraft [33], a food RS for the elderly [34], and a menu RS for young children [35]. In comparing these proposals with our developed tool, we can highlight the following distinctions.

Public GYM [26] primarily focuses on recommending physical strengthening exercises at public gyms, neglecting other aspects. In contrast, our tool comprehensively addresses PA, healthy eating, mental health, and sleep quality, aiming to improve the overall quality of life. Furthermore, our tool incorporates validation processes, unlike Public GYM.

PRECIOUS [27], while addressing some dimensions, lacks the comprehensive approach of our tool. Our tool encompasses physical, mental, nutritional, and sleep quality dimensions, promoting an improved quality of life through motivating challenges.

Fit brains trainer [28] exclusively targets cognitive improvement, disregarding other dimensions such as healthy eating, PA, and social activities, which our tool encompasses.

Sworkit Lite [29] does not perform an initial assessment or create personalized user profiles for tailored recommendations. In contrast, our tool utilizes questionnaires and user-specific scores to create profiles and recommend challenges based on individual characteristics and dimension scores.

SAFER [30] has some similarities in terms of user profile creation but lacks the depth and validated questionnaires employed by our tool. Additionally, SAFER only recommends recreational and cultural activities, limiting its ability to comprehensively influence quality of life compared to our tool.

HyperRecSysPA [31] shares a similar validation approach with our tool, involving expert evaluations. However, HyperRecSysPA is specific to patients with arterial hypertension, focusing solely on PA. In contrast, our tool aims to prevent and enhance quality of life across multiple dimensions: PA, healthy eating, mental health, and sleep quality.

Mind Match [32], similar to our approach, uses questions derived from validated questionnaires to assess users. However, there is a distinction in that they solely evaluate one dimension, namely mental health, as opposed to our comprehensive approach that delves into both physical and mental well-being, along with dietary and sleep habits. Furthermore, their tool lacks any indication of validation.

In Mindcraft [33], they do not mention the use of any user assessment questionnaire; instead, they focus on emotional well-being, encompassing mental health and sleep. Moreover, their app receives favorable ratings when using the app. Notably, they employ gamification to engage users with their activities. Their emphasis is solely on mental health and sleep, unlike our proposition, which aims to influence physical activity, mental health, and dietary and sleep habits. Additionally, their tool does not provide users with any form of health assessment in contrast to the comprehensive evaluation conducted in our proposal through standardized questionnaires.

Bundasak et al. [34] simply segregate users into groups to provide dietary recommendations based on their group, without utilizing any validated questionnaire to assess users, nor providing any feedback on their health status.

Namgung et al. [35] conducted an assessment of macronutrient intake by weighing children's meals before and after consumption. Based on the results of these weightings, they categorize them into four groups to tailor menu recommendations accordingly. Once again, this approach appears to focus solely on influencing one aspect of users without addressing their overall health comprehensively.

In summary, our tool stands out by offering a comprehensive approach to promote healthy lifestyle habits, addressing various dimensions and individual characteristics, which is supported by validated questionnaires and input from a multidisciplinary team of experts.

4.2. Limitations and Future Work

This study has certain limitations, including a relatively small sample size for obtaining user profiles and testing the algorithm. High-level athletes have not been considered in making the recommendation. The challenges have been tailored toward the general population, taking into account their specific needs but without creating specific challenges for special groups such as, for example, diabetics. It would be interesting to introduce challenges related to community health, such as brushing teeth three times a day or washing hands before each meal. A fully external validation through external consultancy would be a desirable next step, which we are planning to undertake as soon as we acquire the required resources

5. Conclusions

Upon analyzing the available scientific literature, it becomes evident that the population in developed countries can greatly benefit from simple lifestyle interventions, particularly in terms of primary prevention. These interventions, such as dietary improvements, moderate and vigorous PA, and engaging in social activities, have the potential to prevent the onset of diseases or health issues.

To facilitate this process, a functional system for assessing the major weaknesses of individual users has been developed. Actually, the starting point is a comprehensive assessment of the subjects' health status in various dimensions, including physical and mental health, dietary habits, and sleep quality. This evaluation is derived from well-known and standard tests that are integrated in a simple interface to facilitate the participation of the subjects. Results are obtained in a fully automated manner and, on their own, provide useful information for the users.

Guided by these mentioned assessments (the subjects' health status in physical and mental health, dietary habits, and sleep quality), a ranked list of challenges is generated, prioritizing those with the greatest potential to impact lifestyle. This recommendation process is grounded firmly in robust scientific evidence, safeguarding users' well-being and health. It is important to emphasize that the system output is not restrained to a mere recommendation of challenges or a set thereof; instead, a ordered list of challenges is presented, which is accompanied by quantitative insights. This way, the user may decide the one that best matches his/her interests or desires with a quantitative idea of the possible benefit according to its numerical evaluation.

Empirical validation of the proposed RS indicates its efficacy in suggesting challenges that wield a positive impact on individuals' well-being and lifestyle. Notably, the system successfully bypasses undesirable or unsuitable challenges for each particular user profile.

This proposed model ensures interoperability by defining challenges in an open and formal manner. Therefore, any authorized third party operating within the platform framework would be able to introduce new challenges with no need to alter the underlying models or algorithms. Although initially conceptualized as a supportive component for a comprehensive gamification platform utilizing blockchain technology [43], the success of this software component has led to its independent offering as a standalone tool.

As mentioned above, it is worth noting that this study is part of a wider project aimed at creating a comprehensive platform for assessing and promoting habits in the areas of PA, mental well-being, nutrition, and sleep patterns.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app13179782/s1, The 30-challenge pool introduced in the RS (references mentioned in Supplementary File [13,14,16,18–20,22–25,52–54]).

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