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RESEARCH

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An approach to boost adherence to self-data reporting in mHealth applications for users without specific health conditions

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Abstract

Background The popularization of mobile health (mHealth) apps for public health or medical care purposes has transformed human life substantially, improving lifestyle behaviors and chronic condition management. The objective of this study is to evaluate the effect of gamification features in a mHealth app that includes the most common categories of behavior change techniques for the self-report of lifestyle data. The data reported by the user can be manual (i.e., diet, activity, and weight) and automatic (Fitbit wearable devices). As a secondary objective, this work aims to explore the differences in the adherence when considering a longer study duration and make a comparative analysis of the gamification effect.

Methods In this study, the effectiveness of various behavior change techniques strategies is evaluated through the analysis of two user groups. With a first group of users, we perform a comparative analysis in terms of adherence and system usability scale of two versions of the app, both including the most common categories of behavior change techniques but the second version having added gamification features. Then, with a second group of participants and the best mHealth app version, a longer study is carried out and user adherence, the system usability scale and user feedback are analyzed.

Results In the first stage study, results have shown that the app version with gamification features has achieved a higher adherence, as the percentage of days active was higher for most of the users and the system usability scale score is 80.67, which is categorized as rank A. The app also exceeded the expectations of the users by about 70% for the app version with gamification functionalities. In the second stage of the study, an adherence of 76.25% is reported after 8 weeks and 58% at the end of the pilot for the mHealth app. Similarly, for the wearable device, an adherence of 74.32% is achieved after 8 weeks and 81.08% is obtained at the end of the pilot. We hypothesize that these specific wearable devices have contributed to a decreased system usability scale score, reaching 62.89 which is ranked as C.

Conclusion This study evidences the effectiveness of the gamification category of behavior change techniques in increasing the overall user adherence, expectations, and perceived usability. In addition, the results provide quantitative results on the effect of the most common categories of behavior change techniques for the self-report

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of lifestyle data. Therefore, a higher duration in the study has shown several limitations when capturing lifestyle data, especially when including wearable devices such as Fitbit.

Keywords Behavior change techniques, MHealth, Wearables, Mobile app, Gamification

Introduction

Technology evolves every day, making our life easier and progressing in several fields of study, improving the quality of life. In particular, smartphones have become an essential tool in our daily lives, impacting 7.2 billion users worldwide with more than 70% of them in low- and middle-income countries [1]. Therefore, advancements in mobile computing leads to several opportunities particularly in the field of analytics and healthcare [2]. For example, the improvement in sensor technology and stability in the data collection process, has allowed saving and processing data for multiple analysis, making it possible to monitor our health through mobile health (mHealth) apps [3, 4].

Behavior change techniques and adherence

The prevalence of health-related disorders and noncommunicable diseases (NCDs) in modern society has led to a growing need for long-term clinical assistance [5]. To address this issue, mHealth apps have become popular for public health and medical care purposes, utilizing Behavior Change Techniques (BCTs) to improve adherence to lifestyle changes and chronic condition management [5]. However, adherence rates remain low, with the World Health Organization (WHO) estimating a 50% rate in high-income countries [6]. Nonadherence may be intentional or unintentional, and understanding these determinants is crucial for designing tailored solutions to improve data reporting.

Some of the most common BCTs [7] include self-monitoring, where users track their behaviors (e.g., through health apps); goal setting, which encourages the establishment of clear, achievable objectives (such as step or calorie goals); and positive reinforcement, which rewards progress with badges or achievements. Other techniques, such as social support (e.g., sharing progress within a community), shaping (gradually increasing behavior complexity), and cue-based prompting (e.g., reminders to exercise or take medications), also play key roles.

These techniques contribute to adherence by enhancing motivation, reinforcing behavior through feedback and rewards, and fostering accountability. Self-monitoring and feedback help users track progress, while goal setting and rewards help maintain engagement. Social support provides encouragement, and cue-based prompts make behaviors easier to remember and sustain. Together, these techniques increase the likelihood of long-term engagement by making behavior change more manageable, motivating, and integrated into users' routines.

Motivation

Concerning the impact of BCTs on adherence levels in mHealth applications, the available evidence is insufficient to elucidate how distinct categories of BCTs enhance adherence. The reported adherence when employing the most prevalent BCTs in mHealth applications significantly differs across various studies [8–14]. This variability may be attributed to several factors, including the predominant focus of studies on user cohorts with specific medical conditions, the scarcity of investigations assessing the same app across different versions to discern the influence of diverse BCT categories on adherence, and discrepancies in the duration of studies.

Taking these factors into account, the objective of this study is to evaluate the impact of the gamification category of BCTs for self-report of lifestyle data, which has been barely studied, in the overall adherence targeting a group of users with no specific health condition. As a secondary contribution, the difference in the adherence and the effect of gamification for a longer period of use has been studied.

Background

There are several studies that have included the most common categories of BCTs [15] with short-term pilot trials (i.e. 1 or 2 months) with the objective of assessing the adherence to the proposed mHealth apps. In a study conducted by [8], the authors evaluate the acceptability of a commercial activity tracker (Fitbit) and three modes of reporting daily steps. For that, a two-month period and 51 adults with chronic musculoskeletal pain are considered. Text reporting yielded 79% adherence compared to the 69% achieved with automated calls and syncing of Fitbit. The categories of BCTs considered in this study are feedback and, reward and threat. According to [9] a mean adherence of 65% is achieved with a mobile app that records various health metrics (e.g. glucose monitoring system, pedometer, etc.) of 20 diabetes patients in a one-month period. The objective of the study is to assess the use and the acceptance of a self-management system. The BCTs categories employed by this study are feedback and monitoring, shaping knowledge, comparison of behavior, associations, comparison of outcomes, regulation, and antecedents. A study by [10] proposed a mobile app to remind the intake of medication for college students who had a current prescription for an antidepressant. The duration of the study is one month with 57 students and the authors report an adherence of 76% for the treatment group and 70.4% for the control group. The categories of BCTs implemented in this study include goals and planning, associations, reward and threat and personalization.

Other studies cover longer periods of time (> 3 months) to assess user adherence with mHealth apps for self-data report. In the study proposed by [11], they consider 25 hospitalized patients for acute myocardial infarction and/or percutaneous coronary intervention. Patients used a mobile app and a supporting web interface with the following BCTs categories: goals and planning, feedback and monitoring, and shaping knowledge. The authors report an adherence of 86% and 77% in the two telemonitoring phases. The study conducted by [12] includes 54 Hispanic adults with uncontrolled hypertension are provided with a mobile app with Bluetooth-enabled blood pressure monitor for self-monitoring and electronic medication tray. After 9 months, the authors reported an adherence that ranged from 89.1 to 95.2% for the experimental group. The BCTs categories considered are goals and planning, feedback and monitoring, social support, shaping knowledge, comparison of behavior, associations and reward and threat. Evidence from [13] shows that the seven-month investigation of the effect of a smartphone-based home service delivery of cardiac rehabilitation for 120 post-myocardial infarction patients leads to 94% of adherence compared to the 68% achieved by traditional cardiac rehabilitation. The BCT categories employed by this study include goals and planning, feedback and monitoring, natural consequences, and regulation.

In the last years, there are some works that have also studied the effect of gamification in the user adherence. According to [16], the authors redesign a mHealth app adding gamification for anxiety treatment for 35 children. As a result, an adherence of 68% was reported compared to the 37% reported without gamification features. As reported by [17], 72 patients with metastatic breast cancer completed the study after 3 weeks, achieving a drug adherence of 87.6% in the app version with gamification compared to the 68.5% achieved in the normal version of the app. Similarly, in the work by [18] an mHealth app was developed to improve medication adherence in patients with chronic conditions adding gamification and measuring adherence after three and six months. The results show an adherence of 96.6% over 3 months and 96.8% over 6 months. As demonstrated by [19], medication adherence can be increased including gamification and real-time features for patients with an active tuberculosis treatment in Malaysia. The authors report an adherence of 90.87% compared to a standard score of 80%. The authors of [20] developed a mHealth app for at least one month and 107 asthma patients to register medication intakes. This app includes gamification and social network features, and the authors report a medication adherence between 75% and 82%.

Previous studies (see summary in Table 1) have shown varying adherence rates in mHealth apps, influenced by factors such as study duration and the utilization of certains BCTs. While these studies integrate BCTs to enhance user engagement, the distinct impact of BCT categories on overall adherence has not been thoroughly explored, particularly across short and medium-term periods. Notably, gamification, a key focus of our work, remains largely unexplored in this context. Our research bridges this gap by investigating the synergistic integration of gamification with established BCTs for self-data reporting, contributing novel insights to enhance user engagement in mHealth apps.

Methods and materials

The main objective of this study is to provide end users with an intuitive and effective mHealth application capable of boosting their adherence to health data reporting. This application consists of an approach made up of BCTs that rely on a platform that has been carefully designed with sustainability, scalability, and maintainability in mind. Both the platform and the different approaches used are described below.

Design of behavior change strategies

As a starting point for the design of a general BCT strategy, it is necessary to select the behavior change techniques to be used. Following the review of the state of the art [15] prior to this study, according to their proven effectiveness, it was decided to include techniques in the categories of feedback and monitoring, goals and planning, associations and personalization. Accordingly, a two-approach strategy was considered with the purpose of comparing one approach made up of the most used and effective BCTs in the state of the art with another approach made up of these same techniques but adding gamification, wishing to explore this category.

Thus, two strategies are implemented and evaluated; BCTsv1 which is based on a traditional behavior change techniques (most used and effective BCTs in the state of the art, encapsulated in the categories from 1 to 4) and BCTsv2 which will have the same base, but gamification is added (from point 1 to 5), a category included a few years ago that consists of more innovative techniques.

Table 1 Summary of previous works that make use of mHealth apps for data reporting

Refer- ence	Year	Study duration	Users	Health condition studied	Categories of BCTs	Data captured	Medication intake	Adherence
[8]	2020	2	51	Chronic musculoskeletal pain	Feedback, and reward and threat	Fitbit	No	79%
[9]	2019	1	20	Diabetes	Feedback and monitoring, shaping knowledge, comparison of behavior, associations, comparison of outcomes, regulation, and antecedents	Health metrics (Glucose, pedometer)	Yes	65%
[10]	2015	1	57	Depression	Goals and planning, associations, reward and threat and personalization	–	Yes	76% for the treatment group and 70.4% for the control group
[11]	2015	4.5	25	Acute myocardial infarction and/or percutaneous coronary intervention	Goals and planning, feedback and monitoring, and shaping knowledge	Surveys, quality of life, blood pressure and pedometer	Yes	86% and 77% in the two telemonitoring phases
[12]	2019	9	54	Uncontrolled hypertension	Goals and planning, feedback and monitoring, social support, shaping knowledge, comparison of behavior, associations and reward and threat	Blood pressure	Yes	From 89.1 to 95.2% for the experimental group
[13]	2014	7	120	Post-myocardial infarction	Goals and planning, feedback and monitoring, natural consequences, and regulation.	Wellness, step counter, blood pressure and weight, sleep duration	Yes	94%
[16]	2018	2	35	Anxiety	Gamification, goals and planning and feedback and monitoring	-	No	68%
[18]	2020	3 / 6	243 / 130	Chronic conditions	Gamification, reward and threat, goals and planning	Steps, medication, health measurements, physio exercises, appointments	Yes	96.6% after 3 months and 96.8% after 6 months
[19]	2024	2	71	Tuberculosis	Gamification, reward and threat, self-belief, and goals and planning	Survey, side effects	Yes	90.87%
[20]	2021	1	107	Asthma	Gamification, goals and planning, personalization and feedback and monitoring	Symptoms, questionnaires	Yes	75–82%

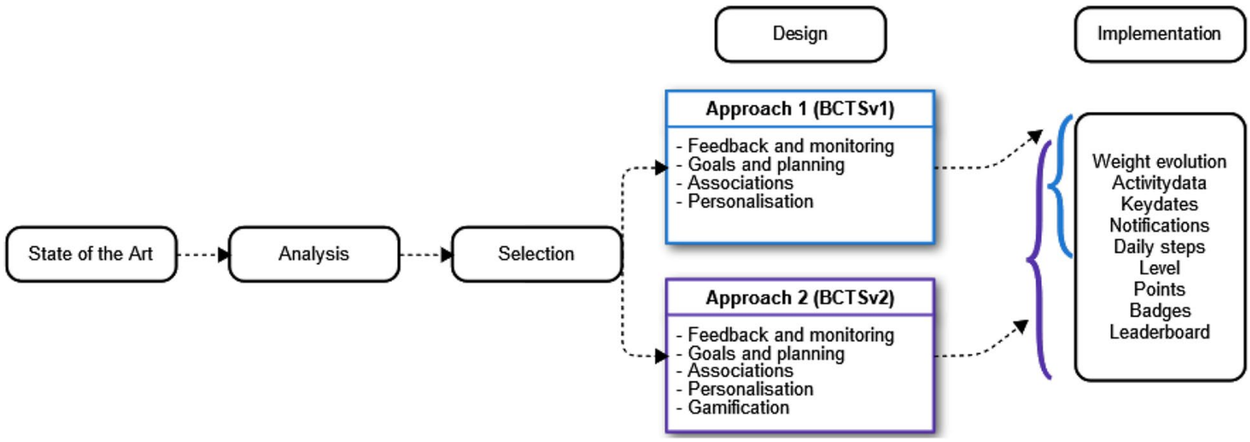


Fig. 1 Two-approach behavior change strategy overview

The previous distribution can be seen in Fig. 1. Below are the five categories along with the techniques that are included in BCTsv1 and BCTsv2, as well as a brief explanation of how these techniques are implemented in our mobile application:

1. Feedback and monitoring: involves providing individuals with information about their behavior and tracking that behavior over time.
2. Monitoring of behavior by others without feedback: record users' behavior with their prior consent through Google's Firebase Analytics [21] library and a wristband.
    - Monitoring of behavior by others without feedback: record users' behavior with their prior consent through Google's Firebase Analytics library and a wristband.
    - Self-monitoring of behavior: ask the user to record at least weekly their weight. and fill in a lifestyle questionnaire.
3. Goals and planning: involves setting specific goals and developing a plan to achieve those goals, individuals can increase their motivation, focus their efforts, and track their progress towards achieving their desired behavior change.
    - Goal setting (behavior): set daily steps goal on the 'home' module and weekly data reporting (weight and lifestyle).
4. Associations: involves pairing a behavior with a specific cue or trigger to create a stronger association between the two. This can help to increase the likelihood that the behavior will occur in response to the cue.
    - Prompts/cues: cue to report weight and lifestyle questionnaire in the specified dates previously displayed in the 'home' module, through push notifications (reminders). Also, to remind the use of the wristband in case of identified inactivity.
5. Personalization: involves tailoring an intervention or message to an individual's specific needs, characteristics, or preferences.
    - Adjusting intervention content to performance: adjusting daily step goals based on the preceding user's steps achieved, using a forecasting algorithm.
6. Gamification: involves incorporating game elements, such as points, levels, challenges, and rewards, into non-game contexts to increase engagement and motivation towards a specific behavior or goal.
    - Earn points: score points for each weight reported and questionnaire sent. Also, for each badge earned. The user's points can be viewed on the 'home' and 'profile' module.
    - Earn badges/levels: obtain a badge for each predefined goal achieved, oriented to the reporting of data and steps achieved. The user's badges can be viewed on the 'profile' module.
    - Leaderboards: the user's ranking and total points are displayed in the 'home' module.
    - Competitions: all users in this study compete against each other, within a defined period of one month. The outcome is the adherence to data reporting.

Architecture

The implementation (Fig. 2) follows a hexagonal architecture as the main methodology for its software design. Moreover, as the effect of adding a new BCTs category (gamification) wants to be measured, two versions of the same app are designed and implemented. The resulting system consists of loosely coupled components that can

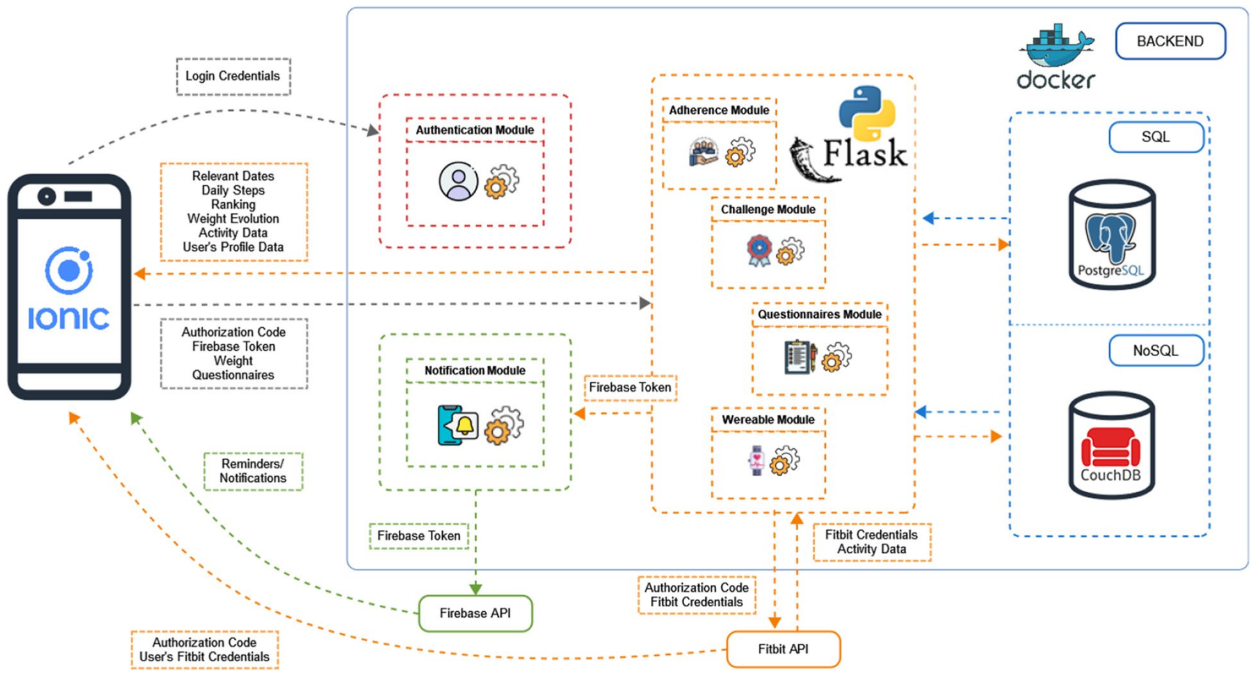


Fig. 2 High-level abstraction of the platform architecture

be easily interchanged by others using the same API. In addition, these components have been developed with open-source technologies that are updated frequently and keep improving over time.

The proposed platform consists of two main components: The first component is a hybrid front-end implemented as a mobile application, developed using Ionic Framework [22] to make the application available to both Android and iOS users, using Angular interface and Cordova to run the application on both platforms. The second component is a back end in charge of managing the business logic, including the authentication process, developed in Python [23] that uses Flask to communicate with the mobile application, and it is responsible for mediating between transactions with persistence or execution of the proposed BCT approaches. The database technologies used were PostgreSQL [24] an open-source relational database which stores all structured data and CouchDB [25] an open-source NoSQL database which uses JSON to store all data whose format is not under our control (e.g. questionnaires, information coming from a wristband). In addition to these two components, we should also mention the wristband tracker and two more third-party components: Firebase API to support the push notifications and Fitbit API for wearable data integration.

Application modules

Going into greater detail about the functionality that this platform offers to end users, then the mobile application has the following functionalities: log-in and log-out; access to information according to user type, that can be BCTsv1 or BCTsv2; linking an activity wristband; gathering patient reported outcomes; following-up on user's critical features; delivering an strategy to ensure users' and visualizing physical activity parameters. The different views (see the main views in Fig. 3) containing the above-mentioned functionalities are presented below:

- Login: allows you to enter the desired language, username and password assigned to the user. When you log in for the first time, it also allows you to change the password.
- Home: this view is broken down into sections, the first is "important dates" which will have the most relevant dates on which the user is expected to submit information (associations and personalization). Then, 'daily step goal' which shows the daily step progress collected by the activity wristband, along with the goal for the day (goals and planning). And finally, the 'ranking' which serves as a reminder of the user's position in the ranking and their total points, followed by the podium of the top 3 users with the most points (gamification). This view has two versions depending on the type of the version of the app,

Fig. 3 Main views of the mobile app: home (left), follow-up (middle) and profile (right)

as in BCTsv1 the user cannot see the ranking section associated with the gamification category.

- Follow-up: this view can be seen by both approaches (BCTsv1 and BCTsv2) and applies the concepts of feedback and monitoring, and associations. The follow-up screen in Fig. 3 is divided into 3 tabs:

  – Weight: allows you to click on the image of the scale to send the weight and observe in the graph the most recent evolution of your weight as well as the total weight change since the first weighing. The system will remind the user to perform this action weekly, although it can be done as many times as the user wants.
  – Diet: the first panel contains 3 questions about the number of hours dedicated to slight, moderate, and intense physical activity. The second panel contains 14 short questions about the diet based on a validated questionnaire for the Spanish population [26].
  – Fitbit: shows the daily evolution of steps, calories burned and sedentary time. This information is provided by the wristband. By clicking on each of the daily evolution graphs, two aggregated evolution graphs will appear.

- Profile: this view is also depicted in Fig. 3 and shows the user's information: id, level, points progress in the current level and the respective ranking position. It is possible to change the profile picture by clicking on it, there are a total of 20 pictures to choose from. Then, it shows in gray all the challenges that the user can achieve, these will be colored when the user completes the challenge. The title and description of how to complete the challenge will be displayed when clicking on your medal. This view is completely dedicated to the BCTsv2 approach which includes gamification, for the BCTsv1 approach it will be disabled and the user will only be able to see their name in the home section.

Table 2 Demographics of participants involved in the user evaluation of the App

Demographic	Group 1	Group 2
Entity	Technology center	University
Period	4 weeks	17 weeks
Age	Mean 28.4 ±6 years of age	Mean 45.5 ±7.96 years of age
#Male	15	20
#Female	16	12
Occupation	23 Researches, 5 Students, 2 Managers and 1 Administrative Assistants	Lecturers

User demographics

In this study we have examined two distinct user groups (see Table 2), both actively engaged in the technology field and closely associated with research environments. The first group is further detailed in Table 3. This table summarizes the demographic data obtained through the pre-questionnaires prior to the intervention, such as: gender, age, occupation, primary expertise (i.e. the main area in which the participant performs), first language, percentage of weekly working hours using computer and internet, computer/mobile literacy (i.e. knowledge in the use of technology) and familiarity with well-being apps. The first group, comprising researchers from a technological center in the Basque Country, was divided into two halves. One segment utilized BCTsv1, while the others were provided with the BCTsv2 app version for a period of 33 days (4 weeks or a month approximately). Upon identifying the app version with the most promising results, the second group, consisting of lecturers from a university of the Basque Country, exclusively employed the optimal app configuration for an uninterrupted period of 119 days (17 weeks). All the participants from both groups work in research environments. The study design is depicted in Fig. 4.

The number of participants is similar in both groups, with the participation of 31 users in the first group and 32 in the second group, which is considered sufficient given

Table 3 Demographic of participants involved in the first stage of the study (Group 1)

Demographic	Result
Gender	15 males, 16 females
Age	Mean 28.4 ±6 years of age
Occupation	23 Researchers, 5 Students, 2 Managers and 1 Administrative Assistant
Primary expertise	18 Computing, 9 Health, 1 Economics, 1 Grants, 1 Mathematics and 1 Administration
First language	20 Spanish, 8 Basque, 2 English and 1 Italian
Average computer usage per week	Mean 49.22 ±10.46
Average Internet usage per week	Mean 59.61 ±23.24
Average level of computer literacy (1 to 5)	Mean 4.32±0.79; Mode: 5
Familiarity with well-being tracking apps (1 to 5)	Mean 3.42±0.99; Mode: 4

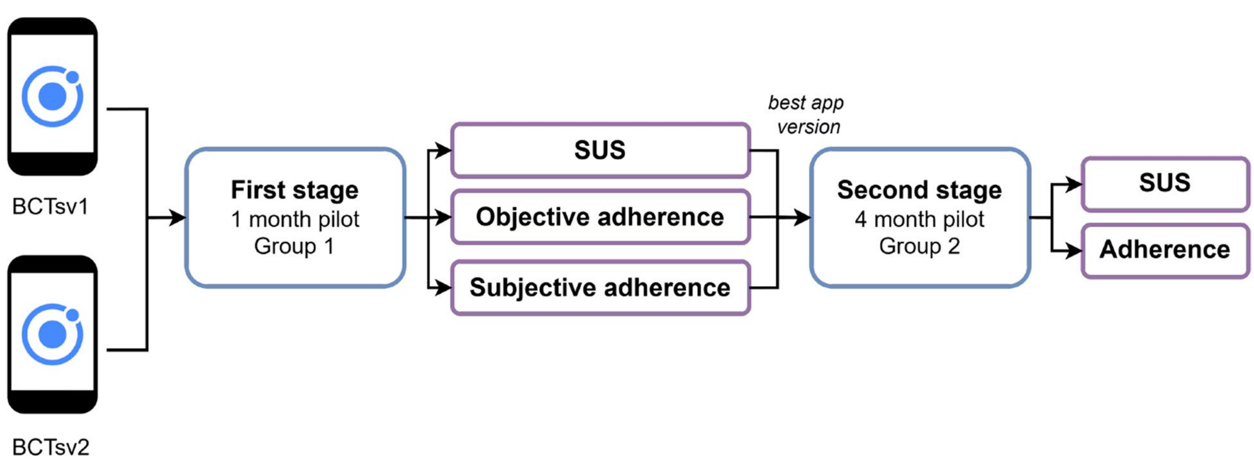


Fig. 4 Two-stage study design

Table 4 Firebase analytics events used for analysis

Name	Description	Measurement
Engagement	Amount of time the application is in the foreground or in focus for at least one second	Minutes
Screen views	Number of times the user switches from one page to another within the application	Quantity
Sessions	Number of times the user interacts with the applications	Quantity
Data Sent	Number of questionnaires sent	Quantity
Days active	Days on which the user interacted at least once with the applications	Percentage

the average of the population sample (n=40.2) taken as the number of participants in state-of-the-art studies [15]. The study protocol was carried out according to the ethical guidelines of the revised 1975 Declaration of Helsinki and approved by the Basque Ethics Committee for Research (CEIm-E), ethical approval code: PI2019130. Written informed consents were obtained from the study participants. All data was anonymized to protect the confidentiality of participants.

In the first stage of the study, an email was sent to all employees at the technology center, while in the second stage, the email was sent to all university staff. Those interested in participating were instructed to approach a group member and complete the informed consent form. Participants of the first stage of the study then filled out a questionnaire that collected information on demographics (e.g., age, sex) and computer usage (e.g., hours per week). After signing the informed consent, participants were provided with a unique identifier and credentials to access the app. Additionally, a Fitbit wearable device was given to each participant.

The mobile app is distributed through Play Store (for Android devices) and App Store (for iOS devices). For the first stage of the study, the app was only accessible for specific users with the beta functionality of these markets. For the second stage of the study, the app was made publicly available for everyone, but inside the app there is no register option, so only users with credentials had access. Both groups used their own mobile device. Wearable devices were provided to the participants.

Evaluation

In this study three evaluation approaches are used to evaluate adherence and user engagement to the proposed app: objective adherence, subjective adherence, and system usability scale. Note that these three evaluation approaches are used for the first experiment to exhaustively compare the proposed two app versions (BCTsv1 and BCTsv2) but only the System Usability Scale (SUS) is used in the second experiment.

Objective adherence

To evaluate objective adherence, Firebase Analytics is used, which collects events automatically through basic interactions with the application. From the set of events, the most significant ones are selected as input to measure user adherence. These will be referred to as variables from now on, summarized in Table 4.

Aggregations are made to facilitate analysis and visualization. Mean is calculated for engagement, screen views and sessions, the sum of the number of completed questionnaires for data sent and finally, the percentage of days with at least one session for active days. It should be noted that these calculations are made for the first experiment 33 days, approximately one month and separately for the two behavior change approaches implemented, BCTsv1 and BCTsv2.

Users with more screen views, sessions, and active days tend to be more engaged with the application and show higher adherence. Conversely, users with fewer screen views, sessions, and active days may demonstrate weaker adherence.

Subjective adherence

The measurement of the user's subjective adherence to the mHealth app involves a comprehensive approach considering various internal and external factors (see Table 5) that may influence consistent user interaction. A brief survey consisting of four questions (see Tables 6 and 7) is utilized to identify factors impacting adherence and their potential causes. The questions address difficulties in remembering to enter data, disinterest in reporting, self-perceived ability to report on time, and frequency of memory challenges in reporting.

The survey is administered twice to two user groups (BCTsv1 and BCTsv2, the gamification approach): first, before interaction with the Fitbit device and app to capture initial adherence perceptions, and second when finishing this first stage of the study. The second stage involves comparing results between groups to assess the impact of gamification on adherence.

A hierarchy is established based on factors detrimental to adherence (see Table 5), with weighted averages calculated for each question to create an "adherence

Table 5 Establishment of factors detrimental to adherence according to their nature

Factor nature	Possible cause	Control level (0–1)
	1.1. Problems with notifications	0.5
Internal (of the application)	1.2. Problems with form submission	0.7
	1.3. Problems with application permissions	0.5
	2.1. Technical failure in the device	0.2
Medium (device)	2.2. Connectivity problems	0.2
	2.3. Deterioration or failure of Fitbit device	0.4
	3.1. Lack of interest in the follow-up of their health or well-being	0.4
From user	3.2 Lack of time	0.1
	3.3. Poor experience or understanding of the user interface of the application	0.5
	3.4. Misuse of the Fitbit device or the app	0.4

Table 6 Breakdown of possible causes of detriment to user adherence in questions 1 to 3

Question number	Question	Possible causes	Average control level
1	Do you have difficulty remembering to enter and/or report data to tracking/wellness applications?	1.1, 1.2, 1.3, 3.1, 3.2, 3.3, 3.4	0.5
2	Are you sometimes disinterested/uninterested in reporting diet or wellness tracking data?	2.1, 2.2, 2.3, 3.1, 3.2, 3.3, 3.4	0.3
3	Do you consider yourself able to always report diet or wellness tracking data, within stipulated times?	3.1, 3.2, 3.3	0.3

coefficient". This coefficient represents the user's ease, constancy, follow-up, and interest in interacting with the app subjectively. Questions are categorized into execution (what the user does) and frequency (how often issues arise) groups, both assigned equal weight. The adherence coefficient for each question is determined by the average level of control multiplied by the group weight.

For YES/NO questions, adherence coefficients are further multiplied by 1 or 0 based on user responses, forming the basis for weighting execution and frequency questions. The entire process is detailed in Tables 5, 6 and 7.

Application usability evaluation and approach acceptance summary

Following the study, a comprehensive questionnaire is conducted, including an extended System Usability Scale (SUS) and additional questions to assess the validity and acceptance of proposed approaches, as done by previous work [27]. The SUS, a reliable tool for evaluating system ease of use, was chosen for its efficiency in collecting statistically valid data and providing a clear score. The SUS questionnaire, comprising 10 items with five response options, was supplemented with two extra questions measuring the Adjective Rating Scale (summarize and better describe the numerical score of SUS) [28] and Net Promoter Score (NPS-assess the likelihood of a user recommending this application to someone else) [29]. Two additional statements assessed the acceptability of implemented approaches. The SUS score was selected because previous studies reporting adherence to mHealth apps with gamification features have also used this scale [30–33].

Jeff Sauro [34] proposed interpreting SUS scores by converting them into percentile ranks through normalization, akin to "grading on a curve". Percentile rankings indicate system performance: 80.3/100 or higher corresponds to an A, suggesting user satisfaction and likelihood of recommendation; around 68/100 represents a C, indicating room for improvement; and 51/100 or below signifies an F, emphasizing the need to prioritize usability.

The generalizability of SUS scores for small sample sizes has been a topic of discussion in usability research. While SUS is often applied to larger samples, studies have shown that it can produce reliable results even with smaller sample sizes [35] demonstrated that SUS scores tend to stabilize with as few as 14 participants. Similarly, [36] indicate that most usability issues are uncovered with a small number of users, suggesting that small samples can still provide meaningful and actionable insights into usability concerns. Although generalizability to larger populations may be limited, the SUS remains a robust and widely accepted tool for evaluating usability in such contexts.

Results

This section, first, evaluates user adherence across both versions of the app (BCTsv1 and BCTsv2) to determine the optimal configuration of BCT categories. A one-month study is conducted, thoroughly assessing adherence to both applications. Subsequently, a four-month study is undertaken using the best app version identified in the initial experiment. This longer-term investigation not only examines sustained user adherence but also evaluates the impact of the proposed gamification techniques.

Impact of gamification in user adherence

In this first experiment, user adherence of both versions of the same apps (BCTsv1 and BCTsv2, the gamification approach) is evaluated in the first group of users. The main objective is to see which combination of the different categories of BCTs yields the best results and, particularly, to assess how the addition of gamification affects the overall user adherence. For that, half of the users are randomly selected to use BCTsv1 whereas the others are provided with BCTsv2, both for a one-month period. Three evaluation approaches are used to compare both versions of the same app: objective adherence, subjective adherence and system usability scale.

Regarding objective adherence, Fig. 5 shows the three quantitative variables extracted from Firebase Analytics and grouped by the app version. A visual inspection of the results shows a differentiable region between BCTsv1 and BCTsv2. For screen views, most of the users using BCTsv2 are located below a screen views number of 0.2, whereas for BCTsv1 most of the users are below 0.4. Regarding the number of times the users interact with the application (sessions variable), in general, for BCTsv1 most of the users are located between 0.3 and 0.4 whereas BCTsv2 users show a uniform distribution between 0 and 0.4. Finally, for the percentage of days active, BCTsv2 exhibits higher values compared to BCTsv1, achieving in some cases more than 40% of the days active. These results suggest that there is room for improvement especially when it comes to the number of interactions with the app. The number of screen views may not represent a negative value, as a lower value can indicate that users know where to find the proposed functionalities in the app. However, the percentage of days active is considered high in some cases, so the goals are set weekly for all the users.

Table 7 Equivalence of control in question 4 (single frequency question)

Question number	Frequency	Control level
4	Never/rarely	1
	Occasionally	0.8
	Sometimes	0.6
	Typically	0.4
	All the time	0.2

As for subjective evaluation, Table 8 summarizes the responses gathered for the different questions and before and after the intervention. The analysis of the fourth question indicates a shift in user experiences between Phase 1 (before the intervention) and Phase 2 (after 30 days of use), as well as differences between the two app versions. In Phase 1, users expressed a medium concern about consistency interruptions, which persisted in Phase 2 but with more varied responses. BCTv2 showed a slight improvement, suggesting that gamification exceeded user expectations, encouraging adherence more than anticipated. The dispersed results in BCTv2 imply diverse user experiences, reinforcing the impact of gamification on user engagement. This aligns with the broader discussion on user adherence, highlighting the significance of gamification in influencing user behavior (Table 8).

The mean SUS scores for our app is 73.96 (B, the top 30% of scores) for the BCTsv1 approach and 80.67 (A, the top 10% of scores) for the BCTsv2 approach, resulting in an increase of 12 points for BCTsv2 considering the mean value of 68. The SUS and usability dimensions have a mean score around 70 for BCTsv1 approach (overall SUS 73.96±19.17, usability dimension 69.01±21.75, and learnability dimension 93.75±11.31) and around 80 for BCTsv2 approach (overall SUS 80.67±7.65, usability dimension 76.67±8.98, and learnability dimension 96.67±5.72). As can be observed, the SUS and usability values follow a similar pattern, while the learnability scores are close to 100, which is true in both cases. This shows that users were able to use the application without any prior explanation.

Regarding the additional last two questions extending the SUS questionnaire, the mean adjective rating values obtained for the BCTsv1 approach ranged between 2 and 6 (awful and excellent), resulting in an average of 5.0±1.28. Then, for the BCTsv2 approach, values were obtained between 4 and 6 (ok and excellent), resulting in an average of 5.22±0.56. Thus, users say that the overall user-friendliness of the app is considered good.

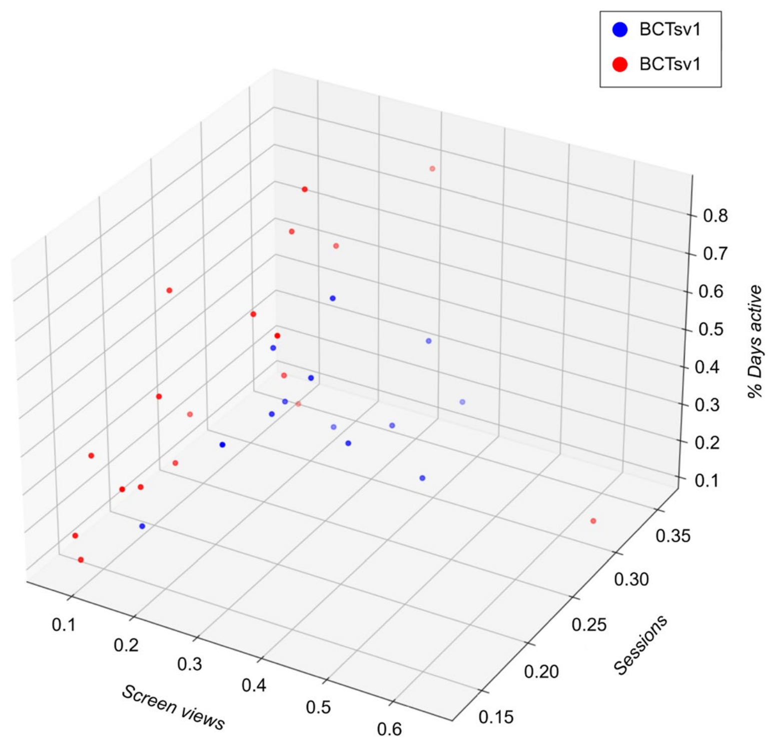


Fig. 5 3D scatter plot with the normalized values of Firebase events

Table 8 Count of the responses gathered for each question to evaluate the subjective adherence

Question	App version	Phase 1 (Before intervention)	Phase 2 (After intervention)
1. Ease of Remembering	BCTv1 (Standard)	10 YES	4 YES
	BCTv2 (Gamified)		9 YES
2. Ability to Report Data	BCTv1 (Standard)	19 YES	7 YES
	BCTv2 (Gamified)		9 YES
3. Interest/Motivation	BCTv1 (Standard)	6 YES	4 YES
	BCTv2 (Gamified)		3 YES
4. Difficulty Consistency	BCTv1 (Standard)	9 "Occasionally", 8 "Sometimes", 12 "Typically"	2 "Never/rarely", 7 "Occasionally", 5 "Sometimes", 3 "Usually"
	BCTv2 (Gamified)		2 "Never/rarely", 5 "Occasionally", 3 "Sometimes", 6 "Usually", 1 "All the time"

The promoter rating scores -likelihood of participants recommending this application to others- for BCTsv1 had values between 1 and 9, with an average of 5.25 ± 2.96, and BCTsv2 had values between 5 and 10, with an average of 6.80 ± 1.47. Having a better average on both components suggests that users of the application with the BCTsv2 approach find the system more usable, efficient, easy to learn and effective. They are also more likely to recommend the system to others, which implies a higher degree of satisfaction and loyalty.

As a conclusion, a deep comparison between both versions of the app has been carried out to understand user adherence and significant differences. Results show a higher adherence reported by the app with gamification, as a higher percentage of active days has been reported in objective adherence and an increase of around 7% has been achieved in terms of SUS score. In addition, prior expectations were significantly exceeded for self-data reporting, reaching an increase of around 70%.

Evolution of the user adherence on a long-term study

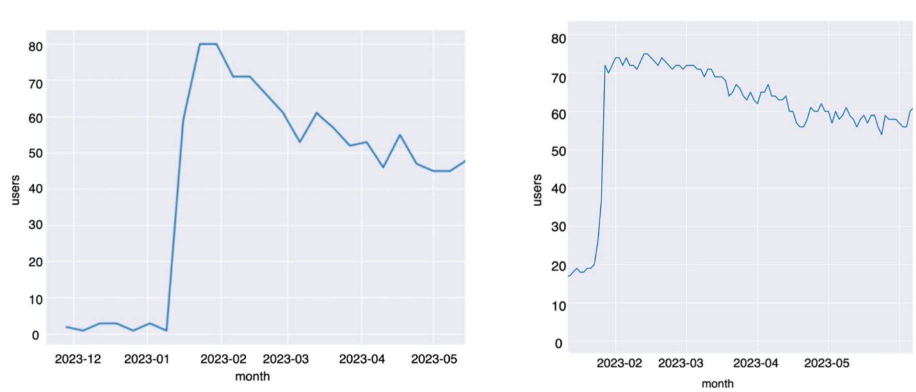
In this experiment, the app version with the highest adherence (BCTsv2, the gamification approach) was intentionally selected and employed, prolonging its use for an extended duration. The primary objective was to see how the adherence of an application with gamification is affected with longer study durations. To achieve this, the subsequent group of users engaged with the app without prior knowledge of the study duration. This alteration of the participants was deliberate to mitigate potential bias, given the familiarity of participants from the previous experiment with the app. It is important to note that around 90 users agreed to participate in the experiment, but as shown in Table 1, only 32 completed the SUS questionnaire, which is nearly the same number of users as in group 1. The adherence to both the app and the wearable device is shown in Fig. 6.

In Fig. 6, the user engagement to both the mHealth app with gamification and the wearable device is shown since the beginning of the pilot at the end of January 2023. In Fig. 6a, the maximum number of users that started using the app is 80, achieving a user adherence of 88.75% after 4 weeks, 76.25% after 8 weeks and 58.75% at the end of the study period (i.e. after 17 weeks). Regarding the wearable device, from a maximum of 74 users, user engagement is 86.48% after 4 weeks, 74.32% after 8 weeks and 81.08% at the end of the study period (i.e. after 17 weeks). Thus, more users were able to use the app at the beginning of the study period but the engagement rate at the end of the pilot is higher for the wearable device.

In addition to user adherence, as the app version with the gamification category of BCTs (BCTsv2) has already been deeply assessed, the SUS scale and the user feedback are used to evaluate the differences with respect to a longer timeframe. Note that 91 users agreed to participate in this experiment but only 53 of them (58.24%) answered the first evaluation questionnaire. In this questionnaire, 62.26% of the participants stated that they were willing to continue in the experiment. In addition, 81.13% confirmed that push notifications were being delivered correctly and 67.92% thought that the short questionnaire about physical activity and diet was sufficient to be filled every month whereas 22.64% selected every two weeks and the remaining 9.43% preferred to answer the questionnaire every week.

However, as no data regarding the age and the sex of the participants was collected until the last questionnaire, the number of participants considered for the final evaluation of the app in a longer study duration is 31. In this questionnaire, 23.68% of the users rate the usability of the app as excellent, whereas 36.84% and 26.64% of the users describe it as good and regular, respectively. The remaining 13.16% consider that the usability is poor. Regarding the techniques included in the app to enhance self-data reporting, the majority, that is 42.11%, said that they are sufficient, whereas 31.58% consider that some could be changed or added and the remaining 26.32% think that these are insufficient. In addition, out of 5, the likelihood of recommending the app to a friend is 2.59.

As for the SUS scalability scale, a score around 63 (overall SUS 62.89±20.29, usability dimension 59.27 ± 21.68, and learnability dimension 77.34 ± 20.19) has been obtained, which is good but could be improved. The best valued category has been the ease to use the app with a 3.68 out of 5 and most of them consider that the app is easy to use and do not need help to use it. Moreover, the users think that the people in general would learn to use it quickly, with a rate of 3.63 out of 5. Regarding the utility of the app to promote self-data reporting, a score of 2.95 was given, having a score of 4 or 5 for 12 users, indicating that the application has effectively cultivated a regular reporting habit among many of its users, with a significant number of individuals consistently contributing data.



a) Users connected at least once per week. b) Daily wearable data per user

Fig. 6 User adherence throughout the 17 weeks from the beginning of the pilot

Finally, some comments were received by the users, being the main positive points: the ranking to promote user motivation and the usefulness of the proposed mHealth app to report data. However, several negative comments were received, which could be related to the SUS score: the features of the smartwatch, the proposed questions which may not be sufficient or complicated to answer, the frequency of the diet questionnaire, less functions than the official Fitbit app, scarce design, no follow-up of the objectives and problems with the reminders. Complaints with the characteristics of the smartwatch have been repeated across many users, stating that the brightness of the screen is very low and the difficulty to read the screen outdoors. Some users also reported that both their own smartwatch, and the Fitbit included in this study, were worn at the same time.

As a conclusion, the evaluation of BCTsv2, the mHealth app with gamification, has been carried out in a longer period. The results show a user engagement of 58.75% and 81.08% at the end of the study to the mHealth app and wearable device, respectively. In addition, many concerns that were not seen in a shorter study have contributed to a decreased usability score compared to the one obtained in the previous experiment. However, 628 answers were received for the diet and activity questionnaire (mean 7.3 and std 6.42 for each user) and 822 answers were received for the weight questionnaire (mean 10.02 and std 11.26 for each user). Regarding wearable data, the app was able to capture full registries for the 17 weeks of 45 users and at least two-month data for a total of 70 users, showing a big difference in data completeness when using an automatic device.

Discussion

In this study, two approaches for behavior change are presented and compared to self-report of lifestyle data. For that, a specific contribution of the proposed mHealth app is the use of BCTs in a data collection and processing platform to collect high quality homogeneous data to subsequently do research in the field of predictive medicine. The accumulation of phenotypic data, environmental and lifestyle factors from healthy, and perhaps diseased, individuals can enable progress in understanding of how the disease will manifest itself and how it will respond to treatment. Also, since the mobile application developed can make use of wearable devices capable of objectively monitoring physical activities, it allows us to include this type of data with the required robustness and quality.

To validate the proposed strategies, an evaluation of objective and subjective adherence and formally defined usability has been carried out; in general, the application has exceeded the expectations of the users, encouraging their adherence and increasing their interest and dedication in sending data and forms related to the follow-up of their health and well-being. Before using the assigned mHealth app version in the first stage of the study, an adherence survey was applied to measure the users' expectations regarding their adherence. At the end of the first stage of the study, that is, after the intervention of the application, these expectations were met or exceeded by approximately 50% in the BCTsv1 approach using traditional BCTs, and in the BCTsv2 approach using gamification. This not only indicates that the application meets the expectations of the users even without the incentives and motivations of scoring, goals, and rankings, but also shows that by implementing these features there is a considerable improvement in user adherence. This was proven given that the qualitative and quantitative results obtained with the BCTsv2 approach were superior to those obtained with the BCTsv1 approach.

After that, a longer study focused on the app version with the highest adherence (BCTsv2 with gamification) has been carried out with a different group of users that started without any indication of the duration. These users were also provided with credentials and with the manual of the app. However, significant differences have been observed between both groups, which could explain why the score in the SUS usability scale has dropped by 20 points, approximately. The learnability dimension gets the highest difference in score, being 96.67 for the first group of users and 77.34 for the second group. Moreover, standard deviation significantly increases, especially for the learnability dimension increasing from 5.72 to 20.19, indicating notable differences in the usability dimension among the users of the second group, The main difference is the duration, as the first group knew that the study would last about a month, so they just needed to use the app with the wearable device and report data frequently. However, in the second group, the duration was not told so the users would only use the app if it contributed to their well-being and if the app effectively encourages them to self-data reporting. Therefore, the user engagement is 58.75% to the mHealth app and 81.08% to the Fitbit device at the end of the study, evidencing the utility of wearable devices for automatic monitoring of user data, compared to the mHealth app, which can be further improved. Note that the user adherence to the mHealth app at the middle of the study is 76.25% compared to the 58.75% reached at the end of the pilot, suggesting that a strategy is required to maintain user engagement over time. This could include approaches such as the intervention of health professionals according to the data reported by the user and proposing new challenges to the user.

During the implementation of the mHealth app, several issues were addressed. The primary issue concerned notifications and data synchronization. Some users reported intermittent notifications, which may indicate a conflict in notification delivery. This could be attributed to errors within the application, misconfiguration of notification permissions, or potential compatibility issues with the users' devices. Regarding data synchronization, issues were reported between the Fitbit device and the application. The main challenge was ensuring consistent and accurate data transfer between the two systems.

In the second group, several issues were identified, emphasizing the significance of selecting smartwatches that not only excel in data capture, as seen in this case, but also provide users with beneficial functionalities. It is crucial to broaden the compatibility of the app beyond the Fitbit brand, incorporating support for the most popular smartwatches. This ensures that users can utilize their preferred devices without the need for simultaneous use of multiple devices. A notable limitation stems from the fact that the official Fitbit mobile app already offers numerous functionalities and data visualization graphs. Consequently, some users may struggle to perceive the additional benefits offered by the proposed application. To address this, when extending the study duration with wearable devices, it is essential to consider the competition posed by other applications. Incorporating distinct features, such as varied visualization panels or the integration of output from an AI model based on the gathered data, can help distinguish the proposed app from others. Addressing these issues is hypothesized to have a positive impact on increasing the SUS usability scale.

Another important consideration is that, due to security measures, participants were not required to provide their email or personal information. As a result, if they forget their passwords, they must contact the administrator for retrieval. It is worth noting that approximately 15 participants discontinued the use of the proposed mHealth app because they didn't reach out when facing credential issues. Additionally, participants reported minor issues, such as not receiving reminders or facing uncertainty on how to complete the questionnaire. However, we hypothesize that the primary factors contributing to a significant decrease in the usability of the proposed mHealth app include the quality of the smartwatch, the use of two wearables simultaneously, and fewer users encountering credential-related issues. It is important to note that the groups of participants differ, with the mean age being lower in the first group. Nevertheless, both groups are accustomed to working with technology daily.

As for the gamification category of BCTs, we believe that the proposed techniques have contributed to an increased user adherence to the mHealth app. The ranking feature, combined with challenges aimed at boosting points, has been reported as a motivating factor for users to self-report data. Additionally, some users not only completed all the challenges but also suggested adding more. Regarding this point, it is noteworthy that no intervention was conducted during the pilot concerning data completeness or the number of challenges achieved. Such interventions, featuring a designated role overseeing user information and a protocol for action and feedback, could have potentially increased adherence among participants. Note that the reported increase in the average SUS score for the app version with gamification features may vary if gamification is combined with other categories of BCTs. In addition, although our focus is on well-being and users without specific health conditions, certain categories of BCTs (e.g., threats) may not contribute to increased adherence if applied in other contexts (e.g., patients with cancer).

The Cronbach's alpha [37] value has been computed to assess the internal consistency of participant responses to SUS scale. In the first stage of the study, a Cronbach's alpha value of 0.87 (good) has been obtained, whereas in the second stage of the study the value is 0.92 (excellent). These scores evidence a high consistency of participant responses. The Mann-Whitney U test [38] has been used to compare the SUS scores reported by the participant in both the first and the second stage of the study. Normality cannot be assumed for the SUS scores reported by the participants (Shapiro-Wilk test, (p-value $>$ 0.05)), thus, a parametric test such as t-test is not used [39]. A comparison of both version of the same app in the first stage of the study do not achieve statistical significancy (p-value $>$ 0.05). The practical effect size, measured by Cohen's d, when comparing the SUS scores of both app versions is 0.47. Cohen's d of 0.47 suggests a moderate effect size between the two groups. Cohen's d is a standardized measure that quantifies the size of the difference between two groups relative to the variability within them. A value of 0.47 indicates a noticeable difference, but not a large one. This moderate effect size could imply some impact on user satisfaction or usability, but may not be strong enough to lead to a significant operational or practical difference in all contexts. A comparison of the SUS scores with Mann-Whitney U tests between the first and second stages of the study revealed statistical significance (p-value $<$ 0.05).

A deep analysis of previous work (see Table 1) has shown that most of the studies (80%) include medication intake modules and the corresponding adherence [40, 41]. Moreover, all the studies in Table 1 target a population with a specific health condition, hindering a direct comparison in terms of adherence to the proposed mHealth app. Thus, this study extends previous work providing evidence on the positive effect of gamification in healthy individuals and the impact of a longer study duration in the overall user adherence.

Finally, the number of registries gathered from wearable devices is the highest. We have complete data for 3 months for 45 users and at least two months for 70 users. Regarding weight records, 16 users exceeded the proposed weekly objective, and 4 users completed it. In total, 31 users reported at least 10 weight registries. On the other hand, the diet and lifestyle questionnaire captured the lowest number of registries. Six users exceeded the proposed weekly objective, one filled it weekly, and a total of 26 users reported at least 10 diet questionnaires. Based on user comments, we acknowledge that a monthly objective for this questionnaire may be sufficient. As a result, a total of 60 users filled in a minimum of 4 questionnaires during the 17 weeks.

Conclusion

In this work, we have presented a mHealth app for self-data reporting including the most used categories of BCTs and, on top of it, gamification techniques to increase the overall adherence. First, a comparative analysis has been done between two app versions that share the same BCTs except for the gamification category. Then, after selecting the app version with the highest adherence, a longer study has been conducted with a different group of participants.

The results show that gamification positively contributes to the user adherence and experience, engaging the users to self-report data and increasing the usability dimension by 7%. In addition, user engagement reaches 58.75% and 81.08% at the end of the study to the mHealth app and wearable device, respectively, evidencing the benefits of including automatic monitoring tools such as Fitbits and underscoring the impact of longer study durations in the mHealth app. Thus, conducting a longer study has showcased several limitations that may have decreased the usability of the mHealth app and that should be considered by researchers and future works when capturing lifestyle data.

Finally, we conclude that the proposed mHealth app with gamification category of BCTs has served to capture diet, activity and health data, with significant differences in the number of registries gathered from wearable devices and manually reported data (i.e. diet, activity, and weight). We have also identified several weaknesses of the proposed approach to be considered as future research such as the characteristics of the smartwatches or the need to update challenges. In addition, more comparatives when having different study durations and categories of BCTs are required when gathering lifestyle data to understand how each category of BCTs contributes to the overall user adherence.

Abbreviations

BCT	Behavior Change Technique
NCD	NonCommunicable Diseases
mHealth	Mobile Health
RQ	Research Question
WHO	World Health Organization
SUS	System Usability Scale

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Authors' contributions

Conceptualisation and Methodology, M.A., A.C., G.E., D.C. and M.T.; Funding acquisition, G.E., U.A, R.B. and I.T.; Project administration, G.E.; Contributions to mHealth App design M.A., A.C., G.E., G.A., and I.T.; Software, M.A., A.C., G.A. and G.E.; Supervision, G.E., D.C. and M.T.; Validation study M.A., G.E., A.C., D.C, M.T., U.A., and R.B.; Data curation, M.A. and A.C. Writing-original draft, M.A. and A.C;

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

The study protocol was carried out according to the ethical guidelines of the revised 1975 Declaration of Helsinki and approved by the Basque Ethics Committee for Research (CEIm-E), ethical approval code: PI2019130. Written informed consents were obtained from the study participants.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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