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ATOPE+: An mHealth System to Support Personalized Therapeutic Exercise Interventions in Patients With Cancer

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ABSTRACT The introduction of mobile technologies in therapeutic exercise interventions has permitted the collection of fine-grained objective quantified information about patients' health. However, exercise interventions generally fail to leverage these data when personalizing the exercise needs of patients individually. Interventions that include technology-driven personalization strategies typically rely on the use of expensive laboratory equipment with expert supervision, or in the self-management of patients to meet the prescribed exercise levels by an activity tracker. These methods often do not perform better than non technology-driven methods, therefore more sophisticated strategies are required to improve the personalization process. In this paper we present ATOPE+, an mHealth system to support personalized exercise interventions in patients with cancer based on workload-recovery ratio estimation. ATOPE+ enables the remote assessment of workload-recovery ratio to provide optimal exercise dosage by means of a knowledge-based system and by combining physiological data from heterogeneous data sources in a multilevel architecture. The results show that ATOPE+ is a system ready to be used in the context of a clinical trial after being tested with patients with breast cancer and conducting an usability evaluation by clinical experts.

INDEX TERMS mHealth, knowledge-based system, smartphone, app, wearable, therapeutic exercise, physical activity, heart rate variability, cancer.

I. INTRODUCTION

Therapeutic exercise (TE) poses a means to address the short and long-term side effects related to cancer itself and its treatment [1], [2]. TE is a subset of physical activity (PA) that consists of structured and repetitive planned movements of activities with a therapeutic aim. The definition of PA is broader, it consists of any movement produced by skeletal muscles with an energy expenditure. Both[1] TE and PA had consistently reported benefits to patients with cancer [3] and they are generally recommended for both prevention and treatment purposes [4]–[6]. There is also strong evidence supporting that, together with medical and surgery treatments, TE improves survival and reduces recurrence and mortality risks [7] due to its positive impact in factors related to quality of life [8]–[10]. This has recently driven the research community to seek after new means to deliver TE interventions in remote environments by leveraging mobile technology [11]. In fact, to date, the literature shows that mHealth PA interventions are a feasible, cost-effective approach to improve overall activity levels, body composition, quality of life and self-reported symptoms in patients with cancer [12] and survivors [13].

The rise of mobile technologies and the Internet of Things paradigm in healthcare has provided means to support

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[1]Throughout this paper, we will differentiate between PA and TE depending on the intervention methods used in the references.

personalized health interventions in remote environments [14], however, the *personalization* process still presents a challenge. Personalizing (or *tailoring*) a TE intervention consists in fitting it to the needs, characteristics or possibilities of each patient with an adapted and evidence-based prescription following for frequency, intensity, time and type [15]. Traditionally, personalization strategies in remote TE interventions were overlooked. Personalization primarily relied on patients' self-management to meet the minimal levels of recommended PA [16], and intervention materials were given as printed booklets, multimedia content or communicated by phone calls. The broad-range nature of these methods is still present in many mHealth interventions [12], [13], thus hampering the introduction of more sophisticated personalization strategies. This opens up opportunities to introduce mobile technologies and monitoring devices to gather objective, comparable and quantifiable information about each patient's health and performance during the intervention process [17], [18], which can potentially be used to tailor and adapt such process to the specific user needs.

In order to deliver a successful personalized TE intervention, it is important to assess the impact of every training session in the patient, the *training load*, to avoid over-training and optimize the prescription dosage in a flexible nonlinear manner. The *workload-recovery ratio* is a key variable to address this issue [19]. The balance of sympathetic and parasympathetic outputs, typically measured using heart rate variability (HRV), plays a key role in the workload-recovery ratio [20]. Consequently, HRV is useful to estimate TE load [21]. However, since HRV measurement typically requires lab equipment, namely an ECG (electrocardiography) [22], any personalization process often becomes tedious and expensive. Fortunately, HRV monitoring has been consistently validated in several types of remote environments with multiple devices and participants [23]–[25], thus enabling its use in TE interventions to estimate workload-recovery ratio. There are also studies using HRV in patients with cancer [26], [27], however, and to the best of our knowledge, there are no prior works using HRV to measure training load in patients with cancer.

Despite the potential benefits of using HRV, it must be noted that HRV could be influenced by many other factors such as physiological and genetic conditions, diseases, lifestyle habits and even external factors [28]. Stress, sleep and fatigue are the factors getting more attention from the research community [29]. Studies using HRV to measure training load in other populations normally omit the role of these other factors that may have high influence in patients with cancer and survivors [22], [30]–[36]. These factors influencing HRV typically need to be assessed with their gold-standard but, fortunately, there are already successful alternative previous experiences when measuring these factors in patients with cancer in remote environments [37]–[40].

In the light of these opportunities, we present ATOPE+, an mHealth system to support personalized therapeutic exercise interventions in patients with cancer. ATOPE+ represents the technological drive of the ATOPE trial [41]. The proposed system enables the remote assessment of workload-recovery ratio to provide optimal exercise dosage by means of a knowledge-based system. With the automatic generation of personalized training prescriptions, ATOPE+ allows us to provide flexible nonlinear periodized exercise prescription (as opposed to linear periodized), minimizing the risk of over-training throughout the TE intervention. To our knowledge, ATOPE+ is the first mHealth system combining measures of exercise load (HRV), modulating factors of HRV (recovery, sleep, distress, fatigue), and daily and training-specific physical activity levels (Fitbit activity tracker) to personalize TE interventions in patients with cancer. The contributions of this paper are the following:

1) A novel concept to personalization in TE interventions in patients with cancer by using physiological variables related to workload-recovery ratio in a remote context.
2) A novel mHealth architecture and a description of its implementation supporting the requirements of a TE intervention in patients with breast cancer, consisting of:
   - Heterogeneous physiological data collection: Bluetooth HRV for exercise load, in-app questionnaires for the modulating factors of HRV, and the Fitbit cloud for daily and workout physical activity levels.
   - A multilevel architecture to transform physiological data into useful knowledge: data, information and knowledge management layers.
   - An intelligent knowledge-based system to support the automatic generation of personalized training prescriptions.
3) An usability evaluation of ATOPE+ with experts (physical therapists with TE experience) using the Systems Usability Scale (SUS) and a semi-structured interview.

Overall, ATOPE+ allows clinical experts to simplify knowledge management and decision-making within the context of a TE intervention by integrating in one tool the process of diagnosing and providing patients' with their individual exercise needs.

The rest of the paper is structured as follows. Section 2 gathers related work to mHealth systems in general and applied to cancer. Section 3 describes ATOPE+ in its entirety: requirements, architecture, implementation and use. The results of its use in patients with cancer and of an usability evaluation are presented in Section 4 and discussed in Section 5. Final conclusions and remarks are summarized in Section 6.

II. RELATED WORK

A. mHealth SYSTEMS

There are plenty of mHealth systems in the literature with applications that range from the promotion of healthy

lifestyles to the prevention and diagnosis of very specific diseases [42]. Most of these mHealth systems leverage the concept of body sensor networks (BSN), a particularization of wireless sensor networks (WSN) in the context of body monitoring environments. A BSN consists of interconnected biomedical sensors that enable the monitoring of physiological parameters to serve the basis for personalized health applications. The literature gather many examples, like Physiodroid [43], which based its health recommendations upon ubiquitous monitoring of physical activity and vital signs; or Mining Minds [44], which leveraged context-awareness, knowledge bases and analytics to provide tailored health support through a knowledge-based recommender system.

Some mHealth systems focus on primarily leveraging smartphone capabilities such as AWARE, [45], MyTraces [46] or InCense [47]. AWARE [45] supports context monitoring, i.e. the collection of unobtrusive passive sensor data with the smartphone, and has highlighted the potential of smartphone sensory data in different health applications such as affect monitoring [48] estimating symptom severity in patients with cancer [49]. InCense [46] shares the same approach to context monitoring and used it to assess functional status in the elderly. MyTraces [47] focuses on recording users' interaction with the smartphone and their emotional states.

Context monitoring may be complemented with physiological measures too. For instance, the CASP system [50] combines smartphone sensing with Bluetooth ECG to predict stress via machine learning. The real-time predictions and feedback channels of CASP enabled provide intervention methods too.

B. mHealth IN CANCER

There are several examples of mHealth systems in cancer. For example, BENECA [37] monitored energy balance and healthy lifestyle in breast cancer survivors. BENECA reported good reliability results, however, the participants highlighted the inconvenience of manually recording their meals and activities every day. This is representative of why other works aimed for unsupervised monitoring by means of clinical-grade activity trackers. For instance, one study used accelerometry to assess performance status and quality of life in patients with gastrointestinal cancer [51]; and another study used accelerometry to profile physical activity behavior in cancer survivors with chronic fatigue [52]. Due to the accuracy and reliability improvements of commercial activity wearables [53], other works have replaced the clinical-grade activity tracker with more convenient and affordable off-the-shelf options. For instance, one study [49] successfully combined smartphone sensing, monitoring with commercial activity tracker, and patient self-reports to predict chemotherapy-related symptom severity using machine learning. Nonetheless, the promising yet unclear relationship among all the variables monitored through smartphone sensing and activity trackers to clinical measures such as performance status [51], [54]–[57] or hospitalization risk [58], [59] reflects the need for a more thorough introduction of mobile technology to assess patient needs.

Focusing on PA and TE interventions with patients with cancer, just a few works leverage the mHealth paradigm. A recent systematic review [12] identified twelve randomized controlled trials meeting the characteristics of an mHealth exercise intervention. In most cases, there was no objectively-monitored personalization strategy. One of the studies [60] used a smartphone app and a pedometer for goal management within the context of a physical activity intervention, however, its only purpose was monitoring, making the personalization strategy to still depend entirely on the clinical experts. Another trial [61] compared a smartphone-with-pedometer exercise intervention (*intervention arm*) against a regular-brochure intervention (*control arm*) in patients with breast cancer, and they found no significant differences between the two groups. Both groups received personalized exercise prescriptions depending on initial tests, but the *intervention arm* aimed for a better personalization strategy. The intervention arm used the activity duration recorded by the pedometer in the previous week as a baseline for the next prescription. Thus, the next prescription added the normal prescription to the previous baseline. Both interventions were successful, however, the lack of significant differences between the two arms points out the need of more sophisticated personalization strategies.

III. ATOPE+

ATOPE+ seeks to shed some light in developing novel personalization strategies for physical activity interventions in patients with cancer. ATOPE+ focuses on retrieving relevant information to the workload-recovery ratio of each subject, so that the TE intervention could be optimized. This allows providing flexible nonlinear periodized prescription of exercise depending on how each patient responds to the training. In this section, the requirements, system architecture and system implementation of ATOPE+ are described.

A. REQUIREMENTS

The requirements of digital health systems are well-discussed in the literature, ranging from pure technical aspects [62], [63] to security concerns [64], or addressing what is necessary to deliver a successful intervention [65]. The requirements of ATOPE+ thrive on them, but more specifically on the need to deliver personalized TE intervention in patients with breast cancer. The definition of these requirements was conducted through several meetings among the computer scientists, engineers and physical therapy professionals co-authoring this article at the beginning of the collaboration, and further refined as the development of ATOPE+ continued. The European General Data Protection Regulation (GDPR) is also included in the requirements from design [66].

Patients must follow the data gathering protocol under similar conditions every day. Patients should record their HRV in the morning right after waking up and emptying their bladder. HRV must be recorded in a lying position [67], and

a minimum of 5 minutes are required for analysis [68]. To establish a reliable baseline for HRV comparison, a minimum of 5 measures are required in the previous 7 days [69]. Next, patients must record their perceived recovery status, distress, sleep quality and fatigue using questionnaires. Patients must also use a wearable activity tracker to collect their overall and training-specific physical activity levels. These data will be used in post-intervention analysis to differentiate patients depending on the fulfillment of general physical activity guidelines [26], and the level of agreement between the training intensity performed and the one indicated in the personalized exercise prescriptions.

First, to automatically generate the personalized exercise prescriptions according to expert knowledge, a knowledge-based system is required. The base of rules will determine the frequency, intensity, time and type of the exercise prescription depending on every day patient's data. Nevertheless, some rules may not always apply, so ATOPE+ must provide expert tools to be able to check and change the exercise prescription according to the expert's criteria on how patient's health is evolving. Two interfaces must be available to address the needs of patients and clinical personnel separately and interact with the knowledge-based system.

Patients must have access to an smartphone app to gather their data, interact with the experts, and receive the personalized exercise prescriptions. The smartphone app must allow connection to external devices, such as Bluetooth ECG, and to ask for recovery, distress, sleep quality and fatigue perceptions through in-app questionnaires. Besides, the app must collect and process the minimum amount of data required for the intervention trial, thus meeting the GDPR minimization principle. Patients should be able to follow the data gathering protocol every day, thus the smartphone app must provide a very clear and intuitive flow through it. The number of wearable devices used must be as reduced as possible, as well as the number of questions asked, so that the protocol complexity and amount of time needed to follow it are minimized.

Clinical experts must be able to check patients' data and modify their exercise recommendations. A web interface must provide meaningful visual display of data related to the workload-recovery ratio of every patient along with the exercise prescriptions. The same web interface must provide means for checking and modifying the personalized exercise prescriptions.

ATOPE+ must be able to manage the heterogeneous data sources noted before: Bluetooth ECG, in-app questionnaires and commercial activity tracker. Moreover, ATOPE+ should be able to transform the raw data into useful information, that is, the personalized exercise prescriptions. This collection of data must be as unobtrusive as possible for the patients to facilitate their engagement in the intervention.

Since ATOPE+ is to be used in a context of a randomized trial with multiple patients at the same time, it must be able to deal with high data volumes and the structured, semi-structured or unstructured nature of the collected data. Consequently, data must be stored and processed efficiently to provide agile and efficient responsiveness.

Data persistence must be carefully managed to avoid data loss in likely deviations from the ideal scenario, like no internet connection or Bluetooth ECG disconnection. Therefore, data must be stored locally in the patients' smartphone before being sent to the cloud or server.

Data reliability must be ensured. Some scenarios might be prone to error, specially those regarding HRV measurement, such as ECG misplacement or ECG recording disruption by external events (e.g. a loud noise, a flash light or a phone call). ECG misplacement may be avoided displaying in-app reminders on how to use the ECG device. Disruption risk may be minimized by lowering notification volume levels during the recording. Last, to ensure HRV reliably, HRV signals must be filtered by detecting, removing and interpolating outliers and ectopic beats [70], [71]. Patients should be given the choice to record their HRV again voluntarily if they considered the recording conditions were not to be ideal, or if the automatic HRV processing rejects the validity of the measures.

The vast amount of data generated may help to assess the validity and pertinence of the training plans assigned to each patient. Thus, this data can be used to refine the existing expert-based rules or even create new ones. On the one hand, unsupervised learning algorithms may reveal these unforeseen relationships among the participants and their recovery process using clustering, anomaly detection or rule generation algorithms. On the other hand, supervised learning, specifically classification models combined with feature selection, may help to highlight the most relevant features for the recovery of patients. Building prediction models to assess the recovery of the patients may also help experts in deciding the best exercise prescriptions for patients when comparing best-case vs. worst-case scenarios. Consequently, ATOPE+ must be able to implement intelligent automatic data-driven analysis and provide means to introduce new rules commanding the recommendations.

Finally, it is of utmost importance to ensure the security and privacy of the data. All online communications must be secured and encrypted with available standards. Access to the ATOPE+ centralized server must be protected through firewall. All the data within the system pseudoanonymized and encrypted. The risk for malicious data usage is increasing as sensitive data-driven systems like ATOPE+ emerge. Fortunately, regulatory and legal policies are already taking this into account such as the European GDPR, which is mandatory regulation for our system.

B. SYSTEM ARCHITECTURE

The architecture of ATOPE+ is shown in Figure 1. The first and fundamental element of the architecture is the *smartphone app* (hereafter, just *app*). The app is the main communication channel with the patient, for both gathering data and for receiving exercise prescriptions. The app collects data from three sources: wearable Bluetooth ECG,

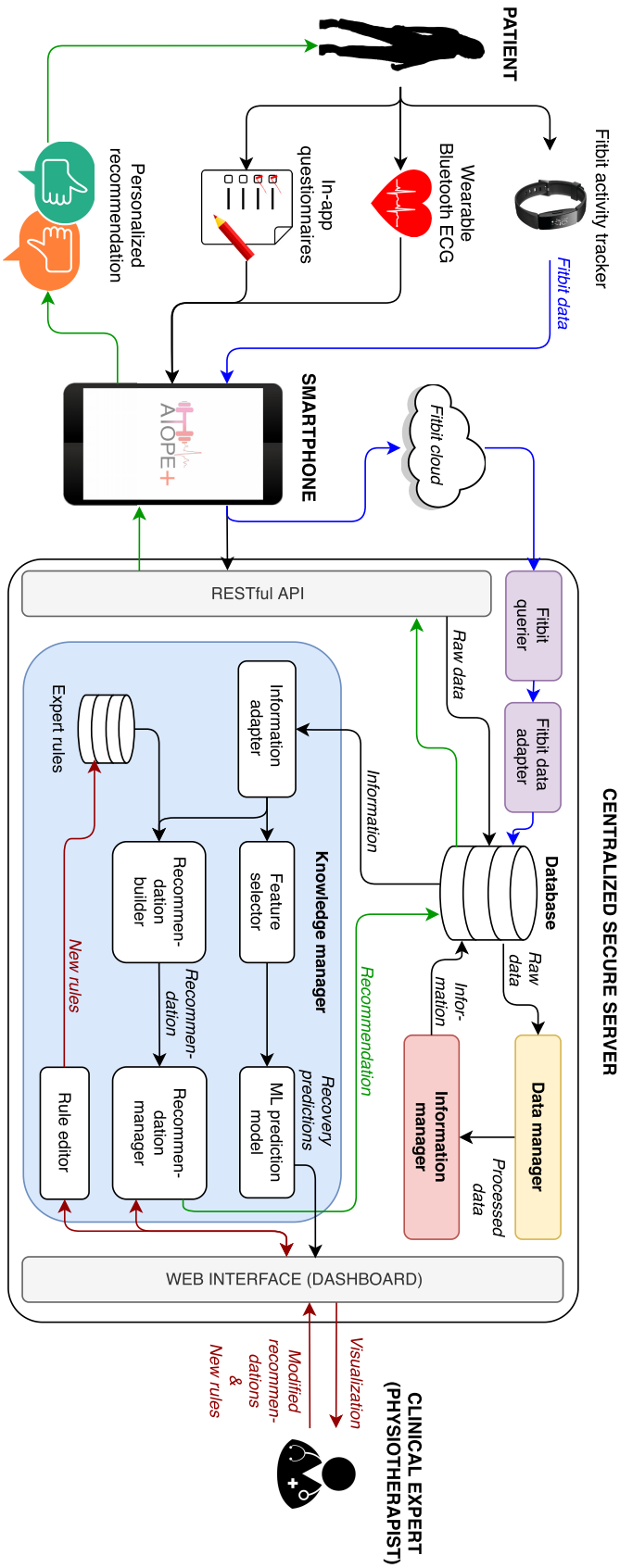


FIGURE 1. System architecture.

in-app questionnaires, and a Fitbit device. ECG and questionnaire data are collected directly through the app, and stored in a local database to ensure persistence of data. If Internet connection is available, data are sent to the server to generate an exercise prescription. The generated prescription is then communicated to the patient's app almost immediately. Last, Fitbit data collected in the *Fitbit Cloud* through the Fitbit app. A description of all the data available is found in Table 1. The *ECG* variables collected are the *time domain*, *frequency domain* and *poincare plot* features, all of them useful for short-HRV measurement (5-min) and to estimate workload-recovery ratio [21]. The modulating factors of HRV are gathered through the *in-app questionnaire* features [28], already successfully measured in patients with cancer in remote environments [37]–[40]. Fitbit's physical activity and sleep data are collected in its entirety as an objective and comparable measure of the exercise load performed by the patient during the day and within training sessions.

The second element of the system is the *centralized secure server*, and it embodies the *knowledge-based system* and the *clinical web interface* stated in the requirements. Several modules comprise the centralized secure server. ATOPE+ downloads Fitbit data with the *Fitbit querier* and incorporates it into the database with the *Fitbit data adapter*. The *Fitbit querier* interacts directly with the Fitbit web API [72] to download the fine-grained activity data of every participant, while the *Fitbit data adapter* adapts and inserts the JSON files returned by the Fitbit API into the *relational database*. A secured and authenticated *RESTful API* enables communications with the smartphone app to capture patient's ECG and questionnaire data. The API also serves as a means to deliver the personalized exercise prescriptions, which are stored once generated. Before building the exercise prescriptions, the raw heterogeneous data needs to be processed in order to extract meaningful information out of it. Raw data enters the *data manager* to be preprocessed and time-synced. Besides, this module cleans the ECG data by automatically detecting, removing and interpolating outliers and ectopic beats, required to ensure correct short-HRV analysis [71]. The *information manager* transforms the processed data into useful information related to different health domains of the patient: *sleep analyzer*, *active and sedentary behavior analyzer*, *training load analyzer*, *fatigue analyzer* and *distress analyzer* (modules not shown in figure for the sake of simplicity). All the information generated gets stored and serves as input to the *knowledge manager* to generate the individual exercise prescriptions. This information comes through the *information adapter* to feed simultaneously the *feature selector* and *recommendation builder*. The *recommendation builder* generates personalized recommendations[2] according to the expert knowledge in the base of rules. The cascading *feature selector* and *machine learning prediction model* represent an active part of the data-driven knowledge by providing recovery predictions for each patient individually. This tool may even assist the expert in evaluating the fitness of rules to patients individually.

The remaining modules of the system revolve around the expert, in our case, a physiotherapist. The *Web interface* allows the expert to: visualize the patient's data gathered; generate new recommendations or modify existing ones for the patients through the *recommendation manager*; and introduce, modify or remove rules in the system through the *rule editor*.

C. SYSTEM IMPLEMENTATION

In this section we detail the implementation for the smartphone app and the centralized secured server of ATOPE+. We also include details on the use of ATOPE+ from the both patients' and experts' perspectives.

1) SMARTPHONE APP

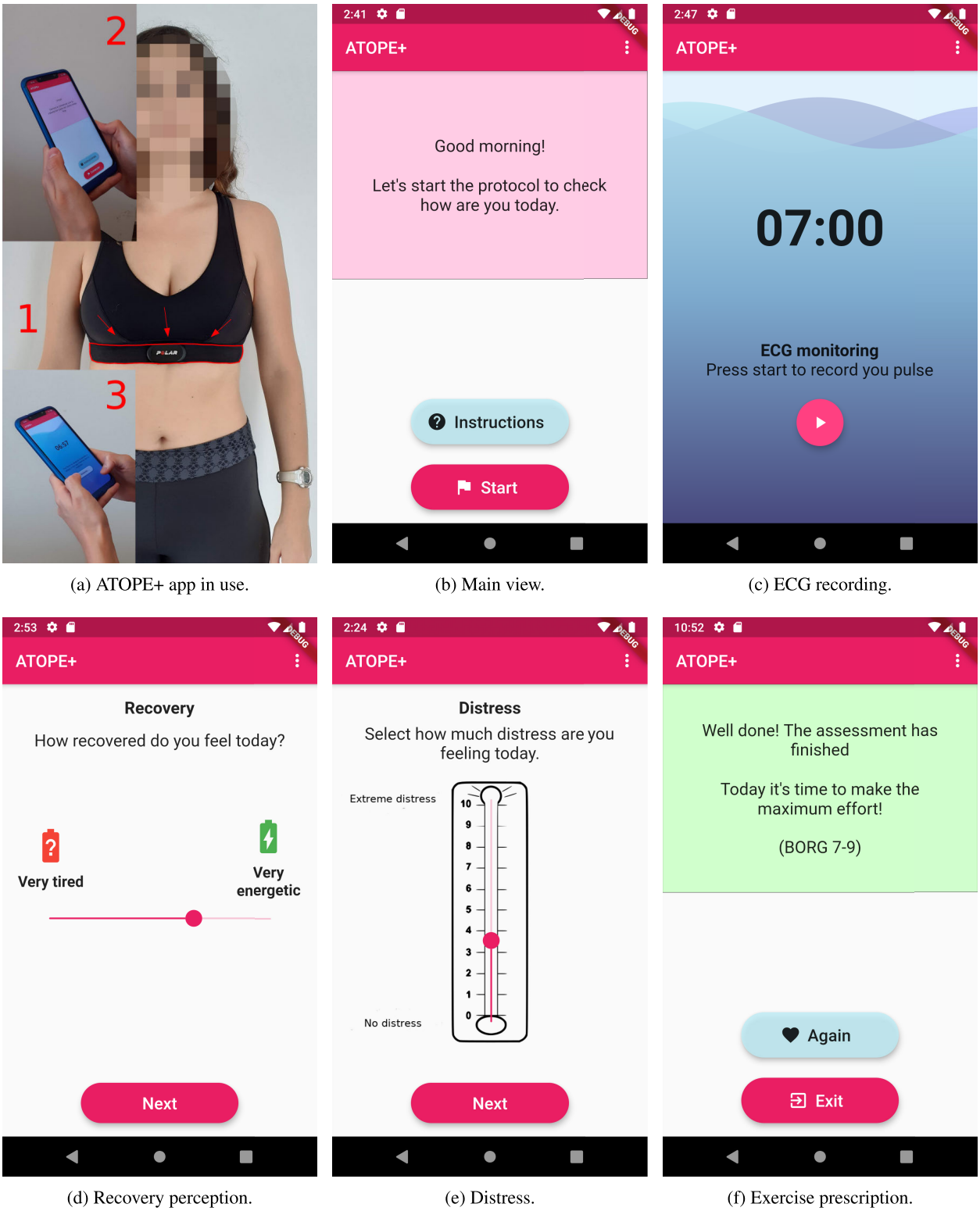
Taking into account the importance of cross-platform app development (essentially Android and iOS), the ATOPE+ app was implemented using Flutter [73] and it is shown in Figure 2. An exemplary use of the app is pictured in Figure 2a, it shows the ECG Polar H10 (Polar USA) position (1) and the start of the HRV recording protocol (2 and 3). Opening the app, the main view ((Figure 2b) welcomes the patient with a message, instructions, and the option to start the protocol. Once the protocol has started, the app scans for available Bluetooth ECG devices to select one. Once the ECG is connected, the view lets the patient to start recording their HRV by pressing a *Play* button Figure 2c. The HRV recording is framed in a 7 minute countdown, out of which only the central 5 minutes are analyzed. Right after the countdown, the app notifies the patient with sound and vibration and the HRV data are sent to the server to be processed. The protocol is followed by the questions for sleep quality, recovery, fatigue and distress perception. Questions for sleep quality, fatigue and recovery perception follow the design pictured in Figure 2d, a continuous Likert scale ranging 0 to 10 with labels in its extreme values. The distress view (Figure 2e) adapts the clinically validated NCCN Distress Thermometer [74] with a continuous slider too. Once the questions are finished, the responses are sent to the server to join the HRV data already processed and receive an automatic personalized exercise prescription, as shown in Figure 2f. This last view also provides the patient with the option to record their HRV again voluntarily, for example, if they think the HRV recording conditions were not ideal.

The ATOPE+ app includes some mechanisms to ensure data transfer to the server. All data are stored locally before being sent. If connection fails at the time of sending HRV or question data, the app will ask the patient to check the Internet connection and try again. Once the Internet connection is back, the data previously stored is sent to the server. This will only happen at the end of the HRV recording or after the last question is answered, thus avoiding disruptions of the

[2]In the case of ATOPE+, the term *recommendation* matches the *personalized exercise prescription*. For the sake of simplicity, we will refer to *recommendations* in the description of the ATOPE+ system.

TABLE 1. ATOPE+ data. All data are timestamped. ECG data are extracted from raw R-R signal with the Aura-healthcare *hrvanalysis* package [75]. Fitbit data are retrieved from its Web API [72] using the *python-fitbit* package [76].

Source	Data	Type	Description
ECG	hr	int	Heart rate (beats per minute).
	rr	int	R-R interval in milliseconds.
	cvnni	float	Coefficient of variation equal to the ratio of sdnn divided by mean_nni.
	cvsd	float	Coefficient of variation of successive differences (rmssd divided by mean_nni.)
	cv_lnrmssd	float	Coefficient of variation of LnRMSSD 7-day rolling average.
	hf	float	Variance in R-R intervals in the high frequency (0.15 to 0.40 Hz).
	hfnu	float	Normalized hf power.
	lf	float	Variance in R-R intervals in the low frequency (0.04 to 0.15 Hz).
	lf_hf_ratio	float	lf/hf ratio as a quantitative mirror of the sympatho/vagal balance.
	lfnu	float	normalized lf power.
	lnrmssd	float	Natural log of the root Mean square of the successive differences.
	max_hr	float	Maximum heart rate.
	mean_hr	float	Mean heart rate.
	median_nni	float	Mean of R-R intervals.
	min_hr	float	Minimum heart rate.
	nni_20	int	Number of interval differences of successive R-R intervals greater than 20 ms.
	nni_50	int	Number of interval differences of successive R-R intervals greater than 50 ms.
	Pnni_20	float	Proportion of NN20 divided by the total number of NN (R-R) intervals.
	Pnni_50	float	Proportion of NN50 divided by the total number of NN (R-R) intervals.
	range_nni	float	Difference between the maximum and the minimum nn_interval.
	ratio_sd2_sd1	float	Ratio between sd2 and sd1.
	sd1	float	Standard deviation of Poincare plot projection on the perpendicular to the line of identity.
	sd2	float	Standard deviation of Poincare plot projection on the line of identity.
	sdnn	float	Standard deviation of the NN (R-R) intervals.
	sdsd	float	Standard deviation of differences between adjacent R-R intervals.
	std_hr	float	Standard deviation of heart rate.
	swc_lnrmssd	float	Smallest worthwhile change of LnRMSSD 7-day rolling average.
	total_power	float	Total power density spectral.
	vlf	float	Variance in R-R intervals in the very low frequency (0.003 to 0.04 Hz).
In-app questionnaires	sleep_satisfaction	float	Sleep satisfaction in continuous Likert scale (0.0 – 10.0).
	sleep_time	int	Reported sleep time (minutes)
	distress	float	Distress in continuous Likert scale (0.0 – 10.0).
	recovery	float	Recovery in continuous Likert scale (0.0 – 10.0).
	fatigue	float	Fatigue in continuous Likert scale (0.0 – 10.0).
Fitbit's activity	steps	int	Steps count.
	intensity	int	PA level (0, sedentary; 1, lightly active; 2, fairly active; 3 very active)
	mets	int	METs (metabolic equivalents of task) expended.
	calories	float	Calories expended.
Fitbit's sleep	sleep_level	string	Sleep stage ('deep', 'light', 'rem' and 'wake').
	nap	int	Number of sleep nap that day (0 is main sleep).
	seconds	int	Duration in sleep stage (seconds).
Fitbit's training session	name	string	Name of activity.
	logtype	string	Type of activity ('auto_detected', 'manual', 'fitstar', 'mobile_run', 'tracker').
	active_duration	int	Duration of physical activity during session.
	duration	int	Duration of session.
	calories	int	Calories expended in session.
	sed_time	int	Sedentary time in session.
	light_time	int	Light intense activity time in session.
	fair_time	int	Fair intense activity time in session.
	very_time	int	Very intense activity time in session.
	max_hr_normal	int	Max HR in normal level.
	max_hr_cardio	int	Max HR in cardio level.
	max_hr_fatburn	int	Max HR in fatburn level.
	max_hr_peak	int	Max HR in peak level (and in session).
	mean_hr	int	Mean hr in session.
	min_hr_cardio	int	Minimum HR in cardio level.
	min_hr_fatburn	int	Minimum HR in fatburn level.
	min_hr_normal	int	Minimum HR in normal level.
	min_hr_peak	int	Minimum HR in peak level.
	time_hr_cardio	int	Time in cardio zone.
	time_hr_fatburn	int	Time in fatburn zone.
	time_hr_normal	int	Time in normal zone.
	time_hr_peak	int	Time in peak zone.



(a) ATOPE+ app in use. (b) Main view. (c) ECG recording.

(d) Recovery perception. (e) Distress. (f) Exercise prescription.

FIGURE 2. ATOPE+ smartphone app. The figures show an exemplary use of the app (a), the most representative views seen throughout the protocol (b-e), and the display of an exercise prescription once the protocol is finished (f).

protocol in the case of connection loss. Besides, if the patient were to exit the app in the middle of the protocol, a warning dialog would pop up to alert the patient they are about to exit the app, and inviting them to continue the protocol.

To ensure data reliability, different strategies are used to handle the HRV and the questions. Regarding HRV, if the server detects a problem while processing the HRV signal (e.g. less than 5 minutes recorded or an excessive amount

of outliers and/or ectopic beats), its response will trigger in the app an error message, asking the patient again to record their HRV. Phone notifications can be very disruptive, thus the smartphone is automatically set up to silent mode while recording HRV.[3] Volumes are brought back to the previous state once finished. Regarding the questions, the patient is forced to answer them before advancing to the next question. This is done by disabling the *Next* buttons at the moment questions are presented, only enabling the *Next* button once the patient has actively selected a score on the slider. Moreover, the initial position of the slider is randomized for every question, which has proven to be an effective mechanism to mitigate anchoring in the responses [77].

Another main concern while implementing the app was usability. We minimized the number of interactions by including the least amount of elements in the screens (see snapshots in Figure 2). Patients are only required to login the first time they use the app to start using it. The protocol follows a straightforward path in the scheme of *one view, one question*, with icons to ease question identifying. There are no preferences to configure, all are controlled from the server side. Font and element sizes are high and controlled to avoid disruption of accessibility options that the smartphone might have enabled.

ATOPE+ was implemented using Flutter [73]. The app uses SQLite for data storage and AES encryption to secure it. The communications with the server are unambiguously authorized with OAuth 2.0 authorization protocol. OAuth 2.0 credentials are first obtained using Deep Linking [78] in Android and Universal Links [79] in iOS. The ATOPE+ smartphone app was tested and built for Android versions over 4.4 (API 19) and iOS 8.0. HRV recordings were tested with a Polar H10 (Polar USA) device over BLE (bluetooth low energy) protocol.

2) CENTRALIZED SECURE SERVER

The centralized secure server of ATOPE+ is responsible for storing and processing the data along with providing communication means for both patients and experts. As stated in the system architecture, the different layers conforming the system transform the data into useful information to, eventually, trigger the expert rules and provide the patients with personalized exercise prescriptions.

Data processing is different for HRV and the Fitbit data. For HRV processing, the *data manager* checks if its length is a minimum of 5 minutes. If so, the data manager looks for outliers in the HRV signal to be removed and linearly interpolated [71]; ectopic beats are also detected [80] and linearly interpolated. Next, the *information manager* extracts time domain, frequency domain and Poincare features out of the clean HRV signal. Relevant features for estimating the workload-recovery ratio like the smallest worthwhile change (SWC) of the natural log of the root mean square of the successive differences (LnRMSSD) and the coefficient of variation (CV) of the LnRMSSD are also extracted for a 7-day time window. The minute-by-minute Fitbit data are aggregated to match daily time windows and the training periods to extract features referred to both time windows.

The base of rules permits defining rules depending on thresholds referred to question responses, HRV features and Fitbit features. For instance, an expert rule may define a *high intensity exercise prescription* if *SWC* is negative and *sleep satisfaction* value is greater or equal to 7.

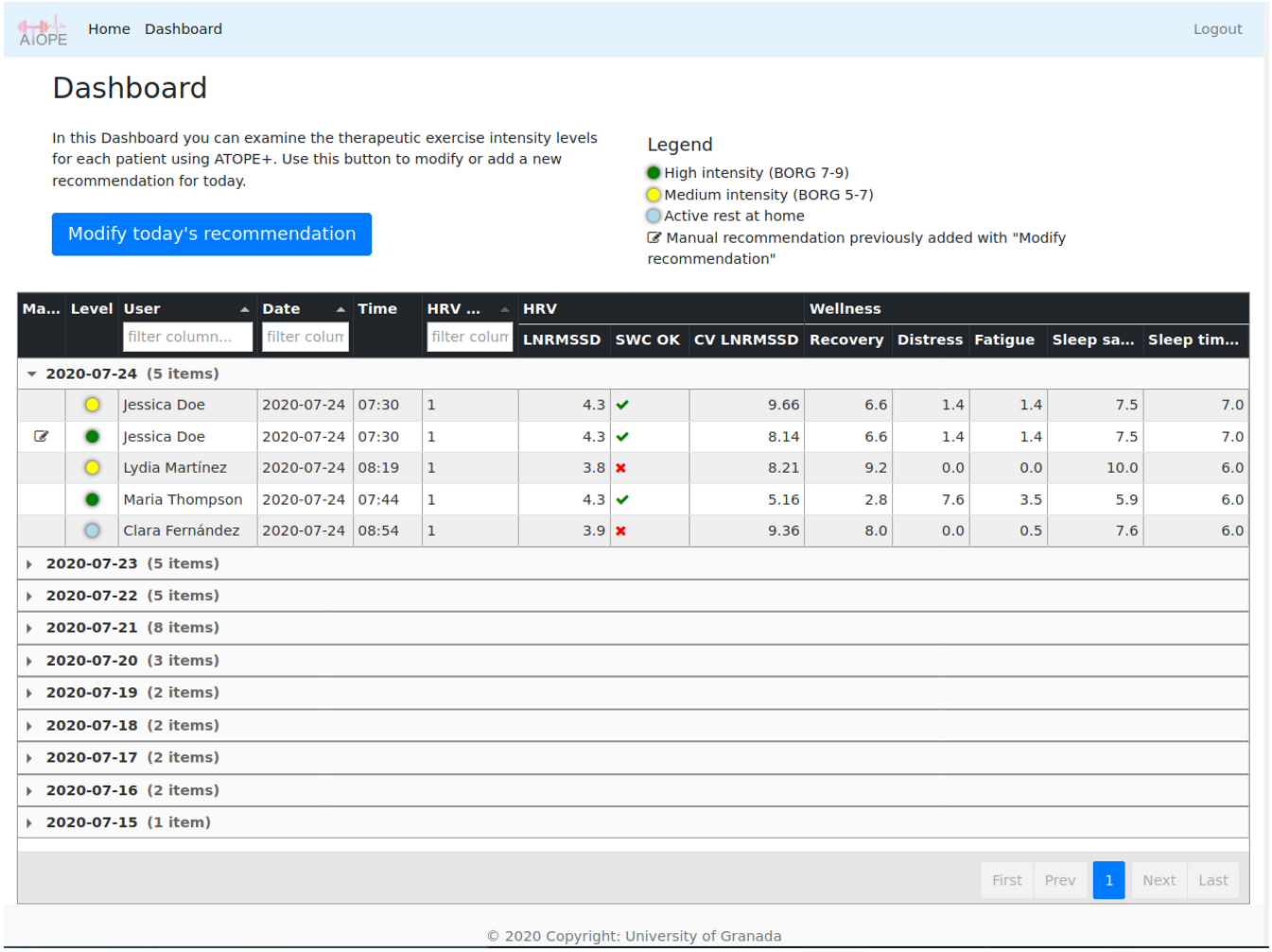
The server implements a Dashboard as the expert web interface (Figure 3). The dashboard displays patient data and the exercise prescriptions given. The main view is shown in Figure 3a. Data are shown in a paginated table that groups the exercise prescriptions day by day. Data can be filtered by patient's name, date and the attempt to record HRV signal. The first column indicates if the exercise prescription shown has been manually added through the modification dialog. The second column shows the exercise description levels (to showcase, three different levels are defined). The table follows with patient's name, date and time of the exercise prescription. LnRMSSD, SWC and CV variables follow are the HRV features presented. Last, all the responses to the questions are presented under the wellness heading.

A dialog to create or modify exercise prescriptions is shown in Figure 3b. The dialog allows the expert to create or modify the exercise prescription for the day checked, by selecting the user and the intensity level of it. The expert can also provide a free comment on why the modification was necessary.

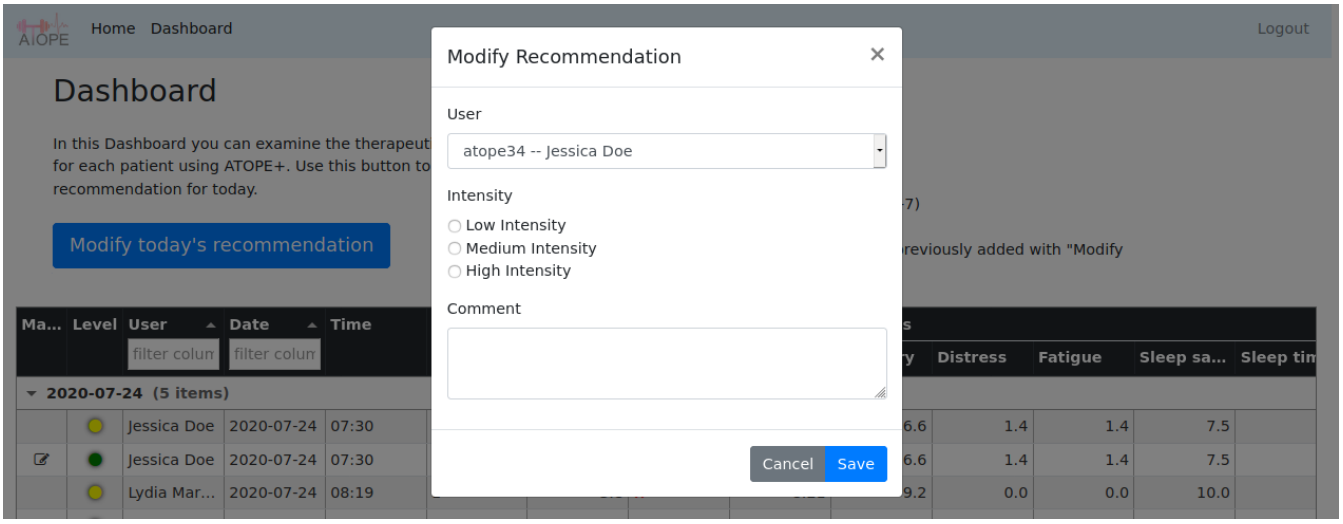
In order to ensure speed, stability, modularity and scalability, the different services composing the ATOPE+ server are implemented using Docker [81]. Docker enables the execution of programs in isolated environments by directly leveraging the host operating system resources. The implementation is divided in three services: *relational database*, *web application* and *reverse proxy*. Each service is a Docker container. All the containers are interconnected through a *Docker network*. The *relational database* runs on a MySQL 5.7 container. All its ports are closed to the outside, and its communications with the web application service are done via a *Docker network*. To ensure high speed performance in queries, data tables are partitioned to the number of participants to be enrolled in the ATOPE trial. The *web application* service is built over Flask 1.0.2 in a Python 3.7 container. This service features role-based authorization for users, an OAuth 2.0 authenticated RESTful API to connect with the ATOPE+ app, and a the ATOPE+ dashboard. Last, the *reverse proxy* service exposes the web application securely to the internet over HTTPS through an uWSGI interface [82]. The host machine runs Ubuntu 18.04 as operating system.

Regarding data security and privacy, Patients' data are gathered and stored meeting the European General Data Protection Regulation. The server is located within the

[3]In order to make the app not too obtrusive, silent mode is just applied to notifications and messages, the volume of phone calls' ring remains unmodified.



(a) Main view.



(b) Dialog for exercise prescription modification.

FIGURE 3. ATOPE+ Dashboard.

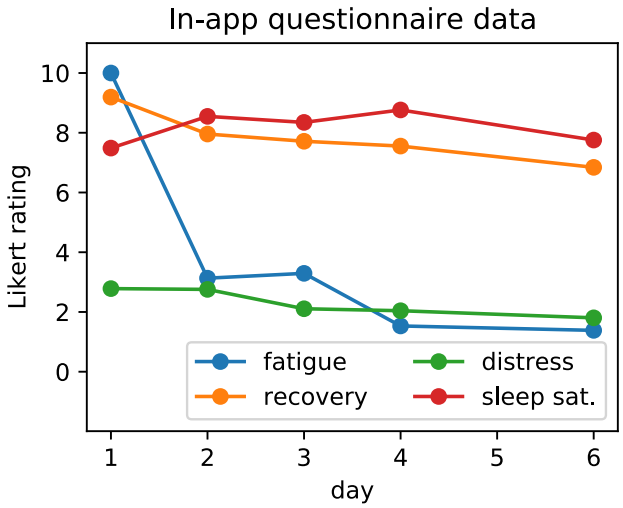


FIGURE 4. Questionnaire data from patient.

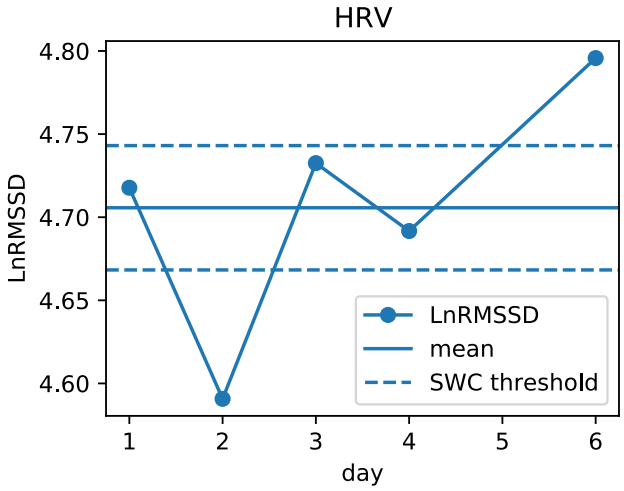


FIGURE 5. HRV data from patient.

facilities of the University of Granada (Granada, Spain) and its physical access is limited to the researchers participating in the ATOPE project and system administrators. All the data stored is pseudoanonymized (random UUID generation) and encrypted (LUKS1 with aes-xts-plain64 encryption). All online communications of the ATOPE+ system (ATOPE+ application and server) are secured via HTTPS connections with SSL/TLS encryption. Moreover, all the communications between the ATOPE+ smartphone app and the server are tokenized via OAuth 2.0 authorization to provide a secure delegated access for every patient. All communications with the database are made locally through a secured (HTTPS) web application. A firewall in the server limits the number of available ports for connections, only enabling ports 22 (SSH) and 443 (HTTPS).

IV. RESULTS

A. DATA SHOWCASE

In order to showcase the possibilities of ATOPE+, we describe some of the data gathered in tests in the following. The data proceeds from two testing scenarios with a total of 16 participants enrolled in TE intervention, out of which 11 were patients recently diagnosed with breast cancer. (Patients: 11 female, age (mean $\pm$ std) 48.36 $\pm$ 12.95 years old, range 27 – 73. Non-patients: 4 female, 1 male, age 28.20 $\pm$ 6.01 years old, range 24 – 40). All the participants recorded their HRV and answered the questions for a duration between 5 and 14 days. All the patients wore a Fitbit Inspire HR during the intervention, out of which seven actually recorded a significant amount of data.

Individual questionnaire and HRV data of a patient are shown in Figure 4 and Figure 5, respectively. These data were obtained through the ATOPE+ app by following the protocol in 5 out of 6 days. A clearly decreasing trend can be seen in the reported *fatigue* variable throughout the days (see Figure 4), which can be related to having finished her last exercise intervention the day before. The rest of the variables (*recovery*, *distress* and *sleep satisfaction*) oscillate around minimal variation. HRV is pictured in Figure 5 through the *LnRMSSD* variable, presenting a growing trend. Repeated daily measures of HRV may allow finding if a *smallest worthwhile change* (SWC) occurs, like the present in day 6. That day, the HRV measure scores out of the SWC threshold, which, for the sake of the example, are defined as $SWC_{th} = mean(LnRMSSD) \pm 0.5 \cdot std(LnRMSSD)$.

Physical activity data of other patient are pictured in Figure 6 and Figure 7. Fitbit physical activity can be represented by METs, steps count (Figure 6) or the time at determined intensity levels (Figure 7). Sleep data are shown in Figure 8 and Figure 9. Total sleep time in a day can be measured (Figure 8), even differentiating categories for the sleep stages (Figure 9). Fitbit sleep detection requires a few days to adequately differentiate among the sleep stages (*wake*, *light*, *deep* and *rem*), that is why, in the first four nights (days 1, 2, 4 and 6), sleep stages are labeled more ambiguously as *restless*, *asleep* and *awake*. Noticing the complete physical activity data collection against the missing sleep data, we may assert that the patient wore the Fitbit activity tracker during her daily activities, but remove it for the nights of days 3, 5 and 10 of her intervention.

Exercise sessions are also recorded during TE intervention. The number of training sessions recorded by five of the patients are shown in Figure 10. Patients like #4 were enrolled in the TE intervention longer, taking up 18 sessions of exercise, whereas others like #2 reached up to 3. This situation happened because patients were enrolled in pre-surgery TE intervention, so its duration could be shortened due to changes in surgery appointments. The distribution of the duration of the intervention can be seen in Figure 11. The duration of the intervention for each participant may vary depending on the intensities and exercises prescribed, therefore slight differences in the distributions can be seen from patient to patient. Since the exercises are timestamped, the physical activity measures shown in Figure 6 and Figure 7 can be directly related to the intervention.

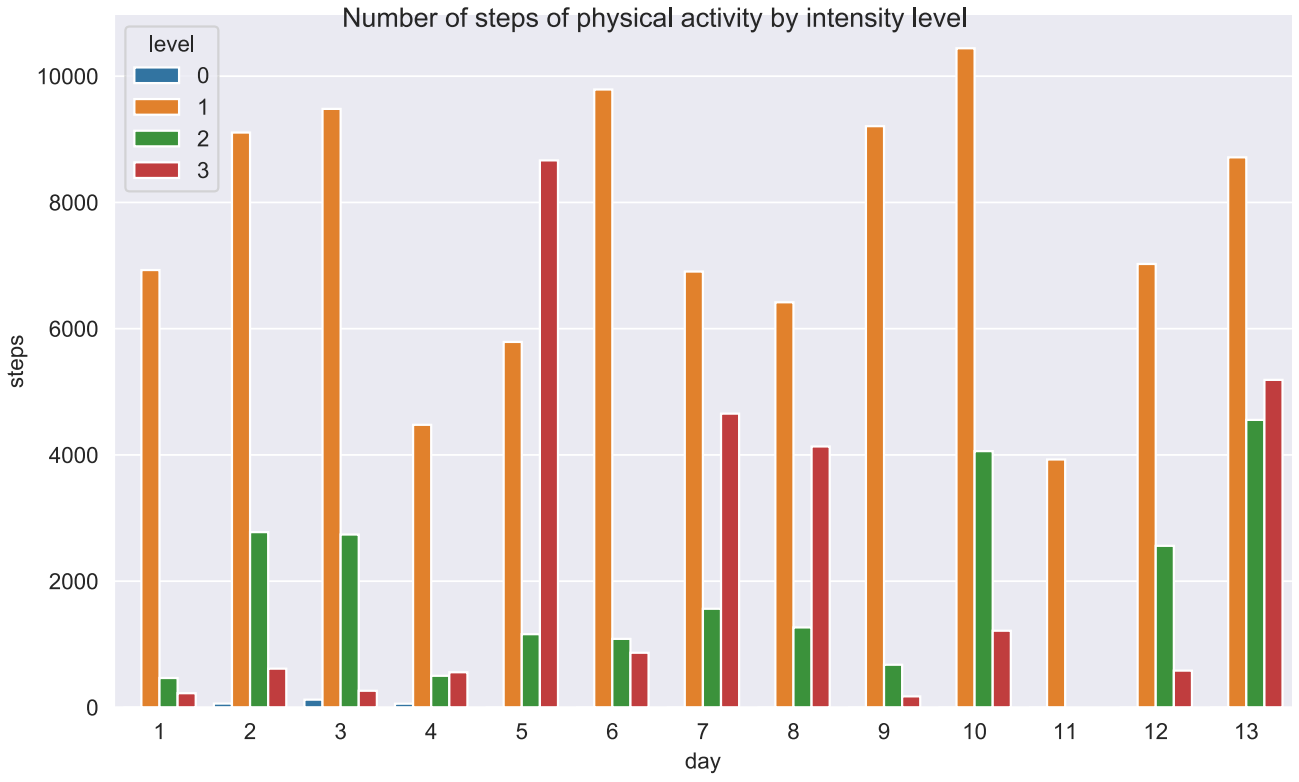


FIGURE 6. Patient steps count data. The levels of physical activity intensity are 0, *sedentary*; 1, *lightly active*; 2, *fairly active*; and 3, *very active*.

B. USABILITY EVALUATION

Eight experts (6 female, 2 male, age (mean ± std) 34.00±7.03 years old), physiotherapists with TE experience in patients with cancer and survivors, used the ATOPE+ app and dashboard for seven days to test the whole system. Usability was evaluated using the Systems Usability Scale (SUS) [83]) and conducting a semi-structured interview [84]. The purpose of using these two methods was to provide a comprehensive vision of the usability of ATOPE+: an objective and comparable result with the SUS, and a less constrained and more descriptive result the semi-structured interview. The usability of the app and the web dashboard were addressed separately.

The SUS scale is a ten-item Likert scale that gives a global view of subjective assessments of usability. Each item of the scale is scored from 1, *strongly disagree*, to 5, *strongly agree*, and the total SUS score is computed out of them, ultimately ranging from 0 to 100. The SUS is easy to administer, performs reliably on small sample sizes, and can effectively differentiate between usable and unusable systems. The SUS allows for usability comparison among systems in research and industry (ISO 9241-11). Sixty-eight points represent the *average* score [85]. The SUS questions are as follows:

Q1. I think that I would like to use this system frequently.
Q2. I found the system unnecessarily complex.
Q3. I thought the system was easy to use.
Q4. I think that I would need the support of a technical person to be able to use this system.
Q5. I found the various functions in this system were well integrated.
Q6. I thought there was too much inconsistency in this system.
Q7. I would imagine that most people would learn to use this system very quickly.
Q8. I found the system very cumbersome to use.
Q9. I felt very confident using the system.
Q10. I needed to learn a lot of things before I could get going with this system.

All the experts filled the SUS individually (Figure 12). The scores were computed and averaged for the app and the dashboard of ATOPE+. Both scored *A, excellent*, that is, over 80.3 points, 90th percentile. The app scored 91.6 ± 7.8 points (average ± standard deviation) and the web dashboard 85.6 ± 20.9.

The answers to the app SUS are shown in Figure 13. All the experts found the app likely to be used frequently (Q1), did not find it unnecessarily complex (Q2) and thought of it easy to use (Q3). Six of the experts did not consider the support of a technical person necessary to use the app (Q4). Every expert considered the functions of the app were well integrated (Q5) and that there was no inconsistency (Q6). Seven out of the eight experts imagined most people could learn to use the

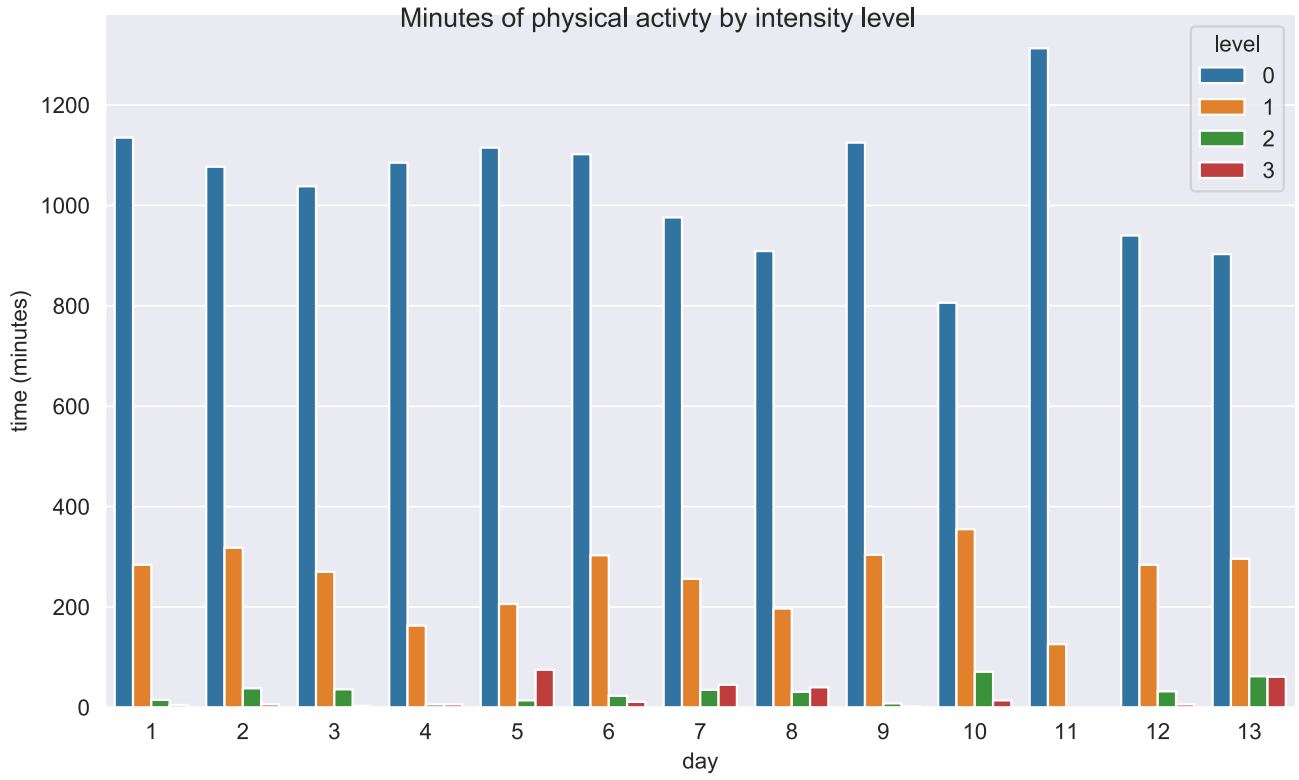


FIGURE 7. Patient PA time data. The levels of physical activity intensity are 0, *sedentary*; 1, *lightly active*; 2, *fairly active*; and 3, *very active*.

system very quickly (Q7). None of the experts found the app cumbersome to use (Q8), all of them were confident using it (Q9) and did not need to learn many things before using the system (Q10).

The results to the dashboard SUS evaluation are shown in Figure 14. Seven of the experts found the dashboard likely to be used frequently (Q1), did not find it unnecessarily complex (Q2) and thought of it easy to use (Q3). Six of the experts did not consider necessary the support of a technical person to use the dashboard (Q4). Seven out of the eight experts considered the functions of the dashboard were well integrated (Q5), that there was no inconsistency (Q6), and that most people could learn to use the system very quickly (Q7). One of the experts found the dashboard cumbersome to use (Q8). Seven experts were confident when using the dashboard (Q9) and five did not need to learn many things before using the system (Q10).

The semi-structured interview was conducted to showcase the impressions of the experts from a more qualitative perspective. Regarding the app, all experts reported from "*good*" to "*very good sensation using the app.*" For example, expert #2 said, "*The overall sensation was very good, very intuitive to follow and with a very good connection to the Polar (ECG device)*", and expert #8 said, "*Quite a good sensation. Very simple to use, clean, with no (unnecessary) ornaments and very intuitive.*" All the experts highlighted the straightforwardness in the use of the app during the interviews. Experts also contemplated the need for training on how to use the app for some of the less skilled patients. As expert #2 reported, "*It is plenty accessible. It will always depend a little on the technological skills of the patient, but they can always receive training during the first and second week of the intervention.*"

To further detail the impressions on the use of the app, the experts were asked about protocol complexity, the clarity of the instructions given and the perspective of the patients using the app during the entire TE intervention. They all agreed on the simplicity of the protocol, the clarity of the in-app instructions and the ease for patients to use it daily.

Some of the experts underlined the importance of delivering and adequate feedback. Quoting expert #4, "*The app may foster patient's autonomy and adherence thanks to the personalized feedback, thus improving her results at the end of intervention.*" Expert #6 reported, "*Patients can learn to use this app easily and engage well, specially if the feedback presented to them is realistic and useful, and they actually see it translated into the (TE) intervention.*"

Taking into account the use of monitoring devices such as the wearable ECG (Polar H10), expert #3 said, "*It is not complicated (to attach the Polar H10), it may be even preferable to sleeping with the wristband (the Fitbit). For patients with breast cancer before surgery this would not be a problem. For those after surgery, they may need some extra attention and be carefully trained on how to use*

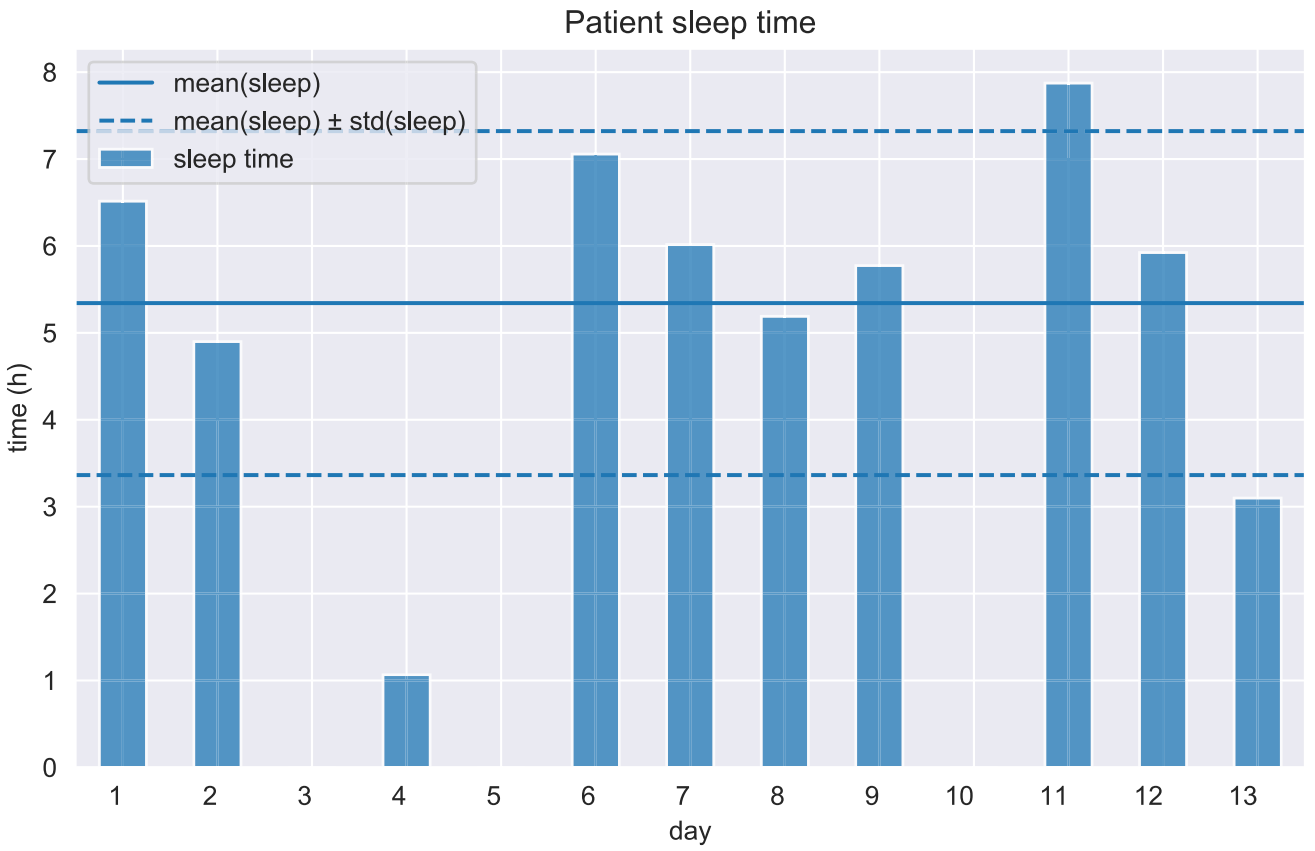


FIGURE 8. Patient daily sleep time.

it.'' Conversely, expert #4 addressed, ''*ATOPE+ needs to be careful in the number of elements participating within the measures, since each one represents a higher grade of complexity, thus rising the probability of errors,*'' right after highlighting the potential of using portable monitoring devices.

Along with the positive feedback, there was place to express concerns, constructive critiques and suggestions. Expert #1 was ''*worried if patients could maintain the daily use of the app.*'' ''*They can just forget, specially once you are in the middle of the treatment and stressed,*'' she continued. Next, the expert suggested, ''*A daily notification in the morning could help to remind the patients to start the protocol right after waking-up.*'' Expert #4 was concerned about the validity of the HRV measures, since measuring conditions can be critical. He proposed, aside from the technical issues of filtering and processing the HRV signal, ''*You can ask the participant, right at the start of the protocol, if the environment conditions are actually ideal, in the form of a checklist: 1) did you empty your bladder? 2) did you drink coffee/tea? 3) are you in a calm settled environment?.*'' Most of the experts agreed that a chat/video-chat with the participant would be also very useful to establish a more solid communication, and the feedback messages could be improved just by mentioning the patient's name. Expert #6 even contemplated the idea of including ''*gamification elements to foster patient's engagement, with very visual feedback.*''

Regarding the web dashboard, all experts reported a good experience while using it and that it was useful to check patients' assessment and make quick decisions on their TE intervention. They all found the option to modify the exercise prescription very intuitive. Expert #3 said, ''*The dashboard is pretty intuitive, you can easily take a quick look at the evaluations of each patient.*'' Some of them requested some features such as the display of data in graphics with trends and visual alerts of anomalies or values out of range.

All the experts agreed on the potential of ATOPE+ to improve the TE intervention process compared to the traditional treatment. In words of expert #7, ''*ATOPE+ may provide a further objective and personalized assessment.*'' Expert #4 said, ''*ATOPE+ addresses the personalization and monitoring process in a new and unprecedented way.*'' Expert #1 added that using ATOPE+ would mean an optimization of resources for both patients and medical personnel:

> *The dashboard is very convenient, it saves a lot of time. The remote personalized assessment alleviates a lot of evaluation tasks from the experts and saves unnecessary journeys from the patients at the medical center to be assessed, thus saving time and resources for us all. Patients could be sent home*

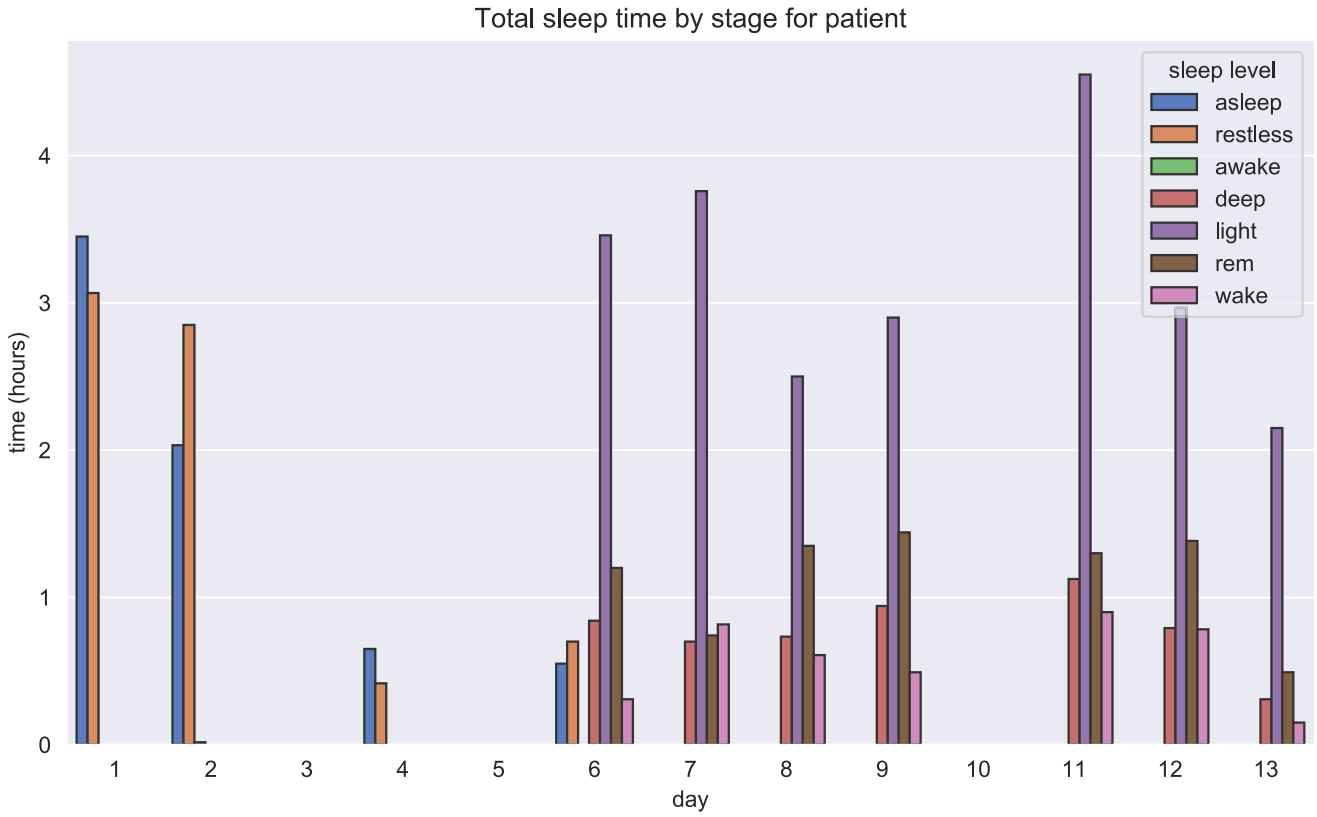


FIGURE 9. Patient sleep time by sleep stage.

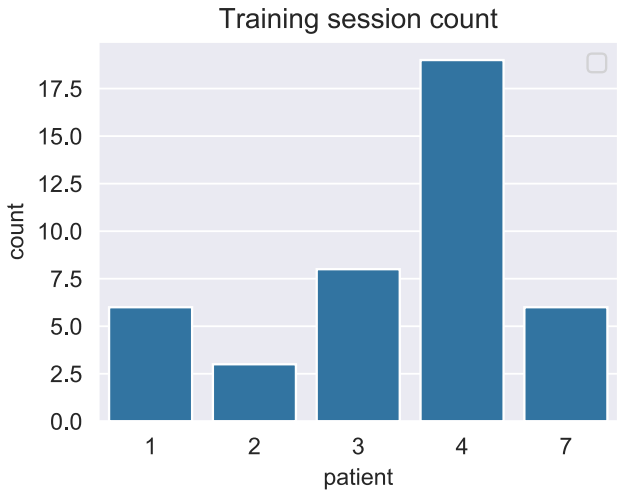


FIGURE 10. Number of training sessions by patient.

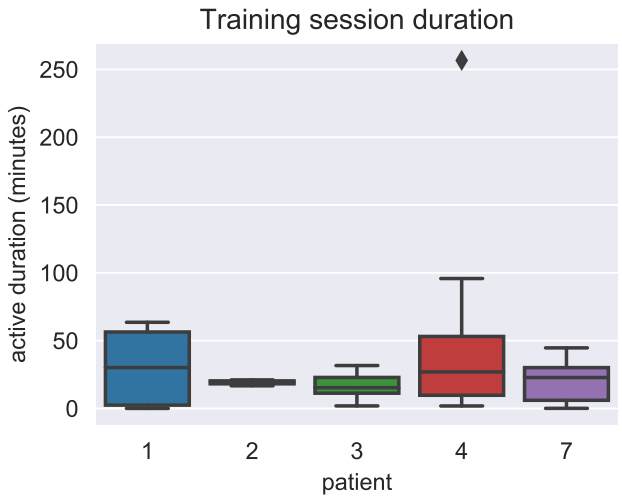


FIGURE 11. Duration of training sessions by patient.

again due to not being in optimal conditions to perform TE that day. (Expert #1)

All the experts acknowledged the possibility of using ATOPE+ in a 100% remote environment such as the COVID-19 pandemic context. They also agreed on the need to make some minor adjustments. Expert #7 commented, "*Since ATOPE+ is focused mainly now in (workload-recovery ratio) assessment, it would be necessary to provide more material to complete the TE program.*" Expert #6 added, "*The engagement with the program would need to be carefully studied. It is not trivial, maybe via technical means such as gamification and/or available communication channels, and also individual supervision by medical personnel.*"

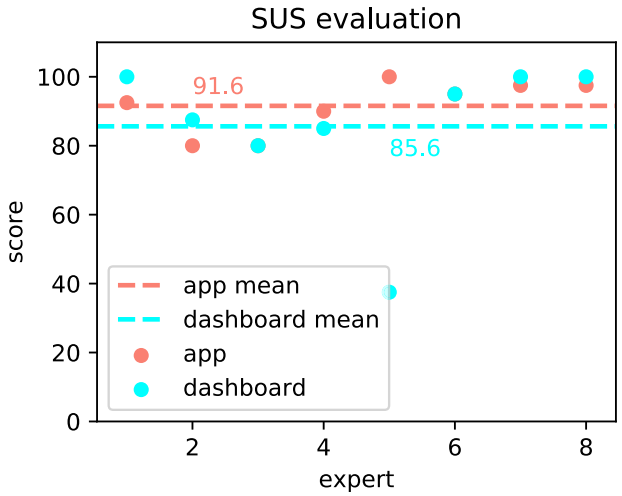


FIGURE 12. SUS score for the ATOPE+ app and dashboard by expert.

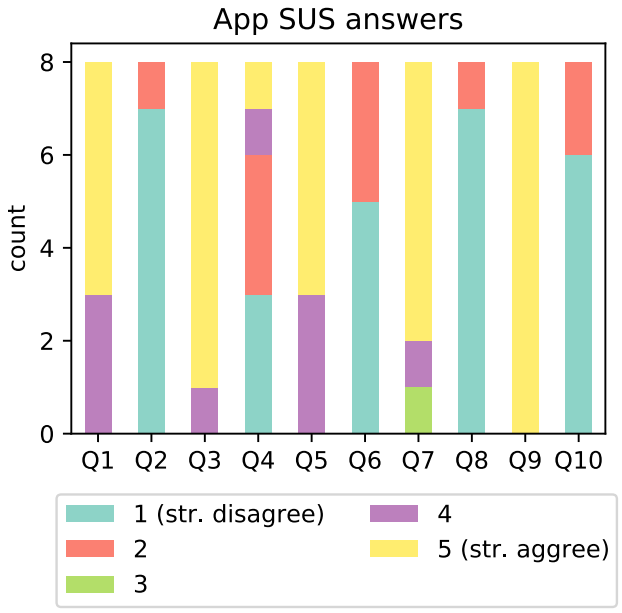


FIGURE 13. App SUS answers. Each bar shows the score count for each of the ten SUS questions. Each color represents the type of answer from 1 (strongly disagree) to 5 (strongly agree).

The experts also foresaw the possibility of extrapolating the use of ATOPE+ to other kinds of patients. Quoting expert #5, "*This methodology could be used with patients with other types of cancer (different to breast cancer), cardiopathy or neurological conditions.*"

V. DISCUSSION

In this paper we presented ATOPE+, an mHealth system to support personalized therapeutic exercise interventions in patients with cancer. The system architecture and implementation were thoroughly described. A data showcase was shown to picture the data gathered by ATOPE+, and an usability evaluation was conducted by clinical experts to show the potential of the system and the usability of its elements. The system, the results obtained, implications and

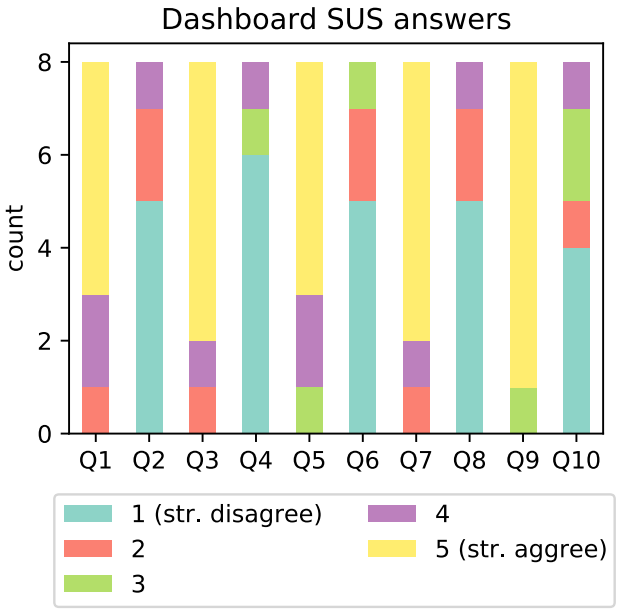


FIGURE 14. Dashboard SUS answers. Each bar shows the score count for each of the ten SUS questions. Each color represents the type of answer from 1 (strongly disagree) to 5 (strongly agree).

recommendations for future studies are further discussed in this section.

A system like ATOPE+ can only emerge from the interdisciplinary cooperation among the physical therapy, medical, engineering and computer science fields. On the clinical side, the relevance of ATOPE+ is rooted in enabling individual remote monitoring of key variables to workload-recovery in patients with cancer. On the technological side, the relevance of ATOPE+ is drawn from the integration of commercial wearable monitoring devices, a data processing pipeline and clinical expert knowledge into a knowledge-based system to automatically provide personalized prescriptions of exercise dosage. Overall, ATOPE+ allows clinical experts to simplify knowledge management and decision-making within the context of a TE intervention by integrating in one tool the process of diagnosing and providing patients' with their individual exercise needs.

ATOPE+ is heavily inspired by the systems presented in the *Related work* section. The multilevel architecture present in most of the mHealth systems referenced [44]–[47], [50] demonstrated its added value handling knowledge, specially after being tested in different health applications such as promoting physical activity, general wellbeing and mental health. The small presence of similar approaches with patients with cancer in TE interventions served as a major impulse for this work, specially noting the lack of sophisticated personalization strategies. Most of the personalization strategies found were based on self-management and/or self-monitoring of physical activity with wearable devices [12]. ATOPE+ takes a different approach by rooting its personalization strategy in the physiological foundations of workload-recovery ratio assessment by means of HRV (and its most relevant modulating

factors: sleep satisfaction, distress, recovery perception and fatige.)

The data showcase presented a sample of the data to be gathered in a TE intervention. The continuous and fine-grained nature of the data may enable the individual analysis of the impact of training sessions in each participant depending on their reported health status and the HRV measured. These data may be analyzed in groups too, allowing to cluster the analysis depending on determined conditions such as *meeting the daily minimum amount of sleep* or the *daily minimum physical activity levels*, for instance. Future work will address the estimation of the workload-recovery ratio in the context of a clinical trial, by testing expert rules built out of expert knowledge. These expert rules will be constructed over all the health variables obtained by ATOPE+.

Usability results were consistent and promising for ATOPE+. The overall good scores in the SUS scale matched the answers to the semi-structured interview, for both the app and the dashboard. All the experts agreed on the potential of ATOPE+ to improve the personalization process in a TE intervention with patients with cancer. Moreover, whilst there was some critique pointing out possible improvements for ATOPE+, none of the commentaries or suggestions were deemed as major issues. This allows us to present ATOPE+ as ready to be used in the context of a clinical trial.

All experts agreed on the ease of use of the ATOPE+ app and the straightforwardness of the data collection protocol. The experts also reported that there was no need for the support of a technical person, that patients would only require a training period to use the app. This is an important result for ATOPE+, since providing an intuitive app experience is imperative to make the system accessible to all the patients, specially those with less technology skills such as the elder generations.

The experts agreed on the possibility of using ATOPE+ in a fully remote environment, only requiring some adjustments on the intervention protocol. This is particularly relevant now in a COVID-19 pandemic context. The immunosuppression often related to cancer treatment may put patients at the very high risk of getting infected with COVID-19. Patients with cancer appear to have an estimated twofold increased risk of contracting SARS-CoV-2 (severe acute respiratory syndrome coronavirus-2) than the general population [86]. Recent literature already recommended reducing this risk by minimizing exposure and prioritizing individualized assistance, suggesting the inclusion of telemedicine strategies as a means to do so [87]. Hence, a tool like ATOPE+ may become of interest in the uncertainty of the following times until the COVID-19 disease is set under control.

The experts shared their ideas on the need for providing objective feedback to patients on their performance. On the one hand, some of the experts were reluctant to include more information than the daily exercise prescription. These experts were concerned about patients becoming too self-aware on their performance and even trying to figure out the inner logic of ATOPE+. On the other hand, other experts were supportive of providing the maximum amount of feedback by wrapping it in a game-based context. These experts considered that a gamification strategy might provide them with tools to promote the fulfillment of the exercise prescriptions. Nevertheless, they also acknowledged that gamification strategies might need to be as tailored as the exercise prescription to become effective [88]. Since ATOPE+ is not a system that focuses on patient's self-regulation, future use of ATOPE+ will limit its feedback to the one provided by the commercial wearable used and the daily exercise prescriptions in the near term.

The SUS dashboard evaluation by expert #5 stands out in Figure 12. This expert was particularly interested in the visual display of data, its trends, the presence of outliers and alerts. Future efforts will focus on providing these tools effectively. The rest of the experts considered that these extra tools would be valuable, but also that the information displayed was sufficient to evaluate the adequacy of the exercise prescriptions.

Our usability results present some limitations since they were performed by eight clinical experts and one patient with breast cancer. We acknowledge that the presented and discussed outcomes may not extrapolate in the context of a complete TE intervention. Despite replication studies were programmed for the preliminary evaluation with patients, this is currently on hold due to the constraints posed by the COVID-19 situation. Future work will adapt the use of ATOPE+ to the current COVID-19 scenario in the context of a clinical trial with patients with breast cancer [41]. Future work will not limit to patients with breast cancer. All the experts foresaw extending the use of ATOPE+ to other types of cancer and diseases, thus opening other lines of work such as lung or colorectum cancer.

VI. CONCLUSION

This paper describes ATOPE+, an mHealth system to support personalized therapeutic exercise interventions in patients with cancer. ATOPE+ enables the remote assessment of workload-recovery ratio to provide optimal exercise dosage by means of a knowledge-based system. Thus, ATOPE+ allows for flexible nonlinear periodized prescription (as opposed to linear periodized), minimizing the risk of over-training throughout the TE intervention. To our knowledge, ATOPE+ is the first mHealth system combining measures of exercise load (HRV), modulating factors of HRV (recovery, sleep, distress, fatigue), and daily and training-specific physical activity levels (Fitbit activity tracker) to personalize therapeutic exercise interventions in patients with cancer. Overall, ATOPE+ allows clinical experts to simplify knowledge management and decision-making within the context of a TE intervention.

ATOPE+ presents a novel concept to personalization in TE interventions in patients with cancer, by using physiological variables related to workload-recovery ratio in a remote context. The architecture of ATOPE+ is designed

to collect physiological data from heterogeneous sources (wearable ECG, in-app questionnaires, Fitbit cloud), transform the data into useful information, and provide individual exercise prescriptions by means of an knowledge-based system.

Multiple tests with patients with breast cancer in TE intervention were conducted successfully. An usability evaluation was conducted to determine how medical personnel and patients would receive ATOPE+. Results showed good satisfaction with the tool as simple, straightforward and easy to use. The experts perceived ATOPE+ as a promising tool to improve therapeutic exercise evaluations. Future work will include the use and validation of ATOPE+ in the context of the ATOPE clinical trial with patients with breast cancer. Our long-term research will also aim to develop and describe the most relevant variables related to the workload-recovery ratio that influence the decision making when prescribing exercise dosage in patients with cancer.

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REFERENCES

[1] R. Ballard-Barbash, C. M. Friedenreich, K. S. Courneya, S. M. Siddiqi, A. McTiernan, and C. M. Alfano, "Physical activity, biomarkers, and disease outcomes in cancer survivors: A systematic review," *J. Nat. Cancer Inst.*, vol. 104, no. 11, pp. 815–840, Jun. 2012.

[2] D. Schmid and M. F. Leitzmann, "Association between physical activity and mortality among breast cancer and colorectal cancer survivors: A systematic review and meta-analysis," *Ann. Oncol.*, vol. 25, no. 7, pp. 1293–1311, Jul. 2014.

[3] D. O. Garcia and C. A. Thomson, "Physical activity and cancer survivorship," *Nutrition Clin. Pract.*, vol. 29, no. 6, pp. 768–779, Dec. 2014.

[4] American Cancer Society. (2020). *Summary of the ACS Guidelines on Nutrition and Physical Activity*. Accessed: Mar. 16, 2020. [Online]. Available: https://www.cancer.org/healthy/eat-healthy-get-active/acs-guidelines-nutrition-physical-activity-cancer-prevention/summary.html

[5] World Health Organization. *WHO|Cancer Prevention*. Accessed: Mar. 19, 2020. [Online]. Available: http://www.who.int/cancer/prevention/en/

[6] A. V. Patel, C. M. Friedenreich, S. C. Moore, S. C. Hayes, J. K. Silver, K. L. Campbell, K. WINTERS-STONE, L. H. Gerber, S. M. George, J. E. Fulton, C. Denlinger, G. S. Morris, T. Hue, K. H. Schmitz, and C. E. Matthews, "American college of sports medicine roundtable report on physical activity, sedentary behavior, and cancer prevention and control," *Med. Sci. Sports Exercise*, vol. 51, no. 11, pp. 2391–2402, Nov. 2019.

[7] M. Pollán, S. Casla-Barrio, J. Alfaro, C. Esteban, M. A. Segui-Palmer, A. Lucia, and M. Martín, "Exercise and cancer: A position statement from the spanish society of medical oncology," *Clin. Transl. Oncol.*, vol. 22, no. 10, pp. 1710–1729, Oct. 2020.

[8] I. M. Lahart, G. S. Metsios, A. M. Nevill, and A. R. Carmichael, "Physical activity, risk of death and recurrence in breast cancer survivors: A systematic review and meta-analysis of epidemiological studies," *Acta Oncol.*, vol. 54, no. 5, pp. 635–654, May 2015.

[9] P. Cormie, E. M. Zopf, X. Zhang, and K. H. Schmitz, "The impact of exercise on cancer mortality, recurrence, and treatment-related adverse effects," *Epidemiol. Rev.*, vol. 39, no. 1, pp. 71–92, Jan. 2017.

[10] L. L. Peterson and J. A. Ligibel, "Physical activity and breast cancer: An opportunity to improve outcomes," *Current Oncol. Rep.*, vol. 20, no. 7, p. 50, Jul. 2018.

[11] A. M. Müller, C. A. Maher, C. Vandelanotte, M. Hingle, A. Middelweerd, M. L. Lopez, A. DeSmet, C. E. Short, N. Nathan, M. J. Hutchesson, L. Poppe, C. B. Woods, S. L. Williams, and P. A. Wark, "Physical activity, sedentary behavior, and diet-related eHealth and health research: Bibliometric analysis," *J. Med. Internet Res.*, vol. 20, no. 4, p. e122, Apr. 2018.

[12] K. Schaffer, N. Panneerselvam, K. P. Loh, R. Herrmann, I. R. Kleckner, R. F. Dunne, P.-J. Lin, C. E. Heckler, N. Gerbino, L. B. Bruckner, E. Storozynsky, B. Ky, A. Baran, S. G. Mohile, K. M. Mustian, and C. Fung, "Systematic review of randomized controlled trials of exercise interventions using digital activity trackers in patients with cancer," *J. Nat. Comprehensive Cancer Netw.*, vol. 17, no. 1, pp. 57–63, Jan. 2019.

[13] A. L. Roberts, A. Fisher, L. Smith, M. Heinrich, and H. W. W. Potts, "Digital health behaviour change interventions targeting physical activity and diet in cancer survivors: A systematic review and meta-analysis," *J. Cancer Survivorship*, vol. 11, no. 6, pp. 704–719, Dec. 2017.

[14] J. Qi, P. Yang, G. Min, O. Amft, F. Dong, and L. Xu, "Advanced Internet of Things for personalised healthcare systems: A survey," *Pervas. Mobile Comput.*, vol. 41, pp. 132–149, Oct. 2017.

[15] K. L. Campbell, K. M. Winters-Stone, J. Wiskemann, A. M. May, A. L. Schwartz, K. S. Courneya, D. S. Zucker, C. E. Matthews, J. A. Ligibel, L. H. Gerber, G. S. Morris, A. V. Patel, T. F. Hue, F. M. Perna, and K. H. Schmitz, "Exercise guidelines for cancer survivors: Consensus statement from international multidisciplinary roundtable," *Med. Sci. Sports Exerc.*, vol. 51, no. 11, pp. 2375–2390, Nov. 2019.

[16] K. H. Schmitz, K. S. Courneya, C. Matthews, W. Demark-Wahnefried, D. A. Galváo, B. M. Pinto, M. L. Irwin, K. Y. Wolin, R. J. Segal, A. Lucia, C. M. Schneider, V. E. Von Gruenigen, and A. L. Schwartz, "American college of sports medicine roundtable on exercise guidelines for cancer survivors," *Med. Sci. Sports Exerc.*, vol. 42, no. 7, pp. 1409–1426, Jul. 2010.

[17] C. M. Kelly and A. Shahrokni, "Moving beyond karnofsky and ECOG performance status assessments with new technologies," *J. Oncol.*, vol. 2016, Mar. 2016, Art. no. 6186543.

[18] M. S. Beg, A. Gupta, T. Stewart, and C. D. Rethorst, "Promise of wearable physical activity monitors in oncology practice," *J. Oncol. Pract.*, vol. 13, no. 2, pp. 82–89, Feb. 2017.

[19] C. Madden, M. Putukian, E. McCarty, and C. Young. (2017). *Netter's Sports Med.* [Online]. Available: https://www.elsevier.com/books/netters-sports-medicine/unknown/978-0-323-39591-5

[20] H. A. Kluess, R. H. Wood, and M. A. Welsch, "Vagal modulation of the heart and central hemodynamics during handgrip exercise," *Amer. J. Physiol.-Heart Circulat. Physiol.*, vol. 278, no. 5, pp. H1648–H1652, May 2000.

[21] P. Kaikkonen, "Post-exercise heart rate variability: A new approach to evaluation of exercise-induced physiological training load," *Stud. Sport, Phys. Educ. Health*, vol. 7, p. 94, May 2015.

[22] F. Shaffer, R. McCraty, and C. L. Zerr, "A healthy heart is not a metronome: An integrative review of the heart's anatomy and heart rate variability," *Frontiers Psychol.*, vol. 5, p. 1040, Sep. 2014.

[23] P. Caminal, F. Sola, P. Gomis, E. Guasch, A. Perera, N. Soriano, and L. Mont, "Validity of the polar V800 monitor for measuring heart rate variability in mountain running route conditions," *Eur. J. Appl. Physiol.*, vol. 118, no. 3, pp. 669–677, Mar. 2018.

[24] D. Hernando, S. Roca, J. Sancho, Á. Alesanco, and R. Bailón, "Validation of the apple watch for heart rate variability measurements during relax and mental stress in healthy subjects," *Sensors*, vol. 18, no. 8, p. 2619, Aug. 2018.

[25] A. S. Perrotta, A. T. Jeklin, B. A. Hives, L. E. Meanwell, and D. E. R. Warburton, "Validity of the elite HRV smartphone application for examining heart rate variability in a field-based setting," *J. Strength Conditioning Res.*, vol. 31, no. 8, pp. 2296–2302, Aug. 2017.

[26] A. Dias Reis, J. B. Silva Garcia, R. Rodrigues Diniz, A. C. Silva-Filho, C. J. Dias, R. D. Leite, and C. Mostarda, "Effect of exercise training and detraining in autonomic modulation and cardiorespiratory fitness in breast cancer survivors," *The J. Sports Med. Phys. Fitness*, vol. 57, nos. 7–8, pp. 1062–1068, Aug. 2017.

[27] D. Ha, A. Malhotra, A. L. Ries, W. T. O'Neal, and M. M. Fuster, "Heart rate variability and heart rate recovery in lung cancer survivors eligible for long-term cure," *Respiratory Physiol. Neurobiol.*, vol. 269, Nov. 2019, Art. no. 103264.

[28] S. Sammito and I. Böckelmann, "Factors influencing heart rate variability," *Int. Cardiovascular Forum J.*, vol. 6, pp. 18–22, May 2016.

[29] Firstbeat Technologies. (2014). *Stress and Recovery Analysis Method Based on 24-hour Heart Rate Variability*. Accessed: Sep. 20, 2020. [Online]. Available: https://assets.firstbeat.com/firstbeat/uploads/2015/10/Stress-and-recovery_white-paper_20145.pdf

[30] M. Gleeson, "Biochemical and immunological markers of over-training.," *J. Sports Sci. Med.*, vol. 1, no. 2, pp. 31–41, Jun. 2002.

[31] C. A. Kushida, M. R. Littner, T. Morgenthaler, C. A. Alessi, D. Bailey, J. J. Coleman, L. Friedman, M. Hirshkowitz, S. Kapen, M. Kramer, T. Lee-Chiong, D. L. Loube, J. Owens, J. P. Pancer, and M. Wise, "Practice parameters for the indications for polysomnography and related procedures: An update for 2005.," *Sleep*, vol. 28, no. 4, pp. 499–521, Apr. 2005.

[32] C. E. Carney, D. J. Buysse, S. Ancoli-Israel, J. D. Edinger, A. D. Krystal, K. L. Lichstein, and C. M. Morin, "The consensus sleep diary: Standardizing prospective sleep self-monitoring," *Sleep*, vol. 35, no. 2, pp. 287–302, Feb. 2012.

[33] S. L. Beck, A. L. Schwartz, G. Towsley, W. Dudley, and A. Barsevick, "Psychometric evaluation of the Pittsburgh Sleep Quality Index in cancer patients.," *J. Pain Symptom Manage.*, vol. 27, no. 2, pp. 140–148, Feb. 2004.

[34] M. J. A. Cordero, A. M. S. López, N. Villar, I. García, M. A. López, A. Pińero, and E. Castell, "Salivary cortisol as an indicator of physological stress in children and adults; A systematic review," *Nutricion Hospitalaria*, vol. 29, no. 5, pp. 960–968, May 2014.

[35] C. Roldán-Jiménez, P. Bennett, and A. I. Cuesta-Vargas, "Muscular activity and fatigue in lower-limb and trunk muscles during different Sit-To-Stand tests," *PLoS ONE*, vol. 10, no. 10, Oct. 2015, Art. no. e0141675.

[36] I. Cantarero-Villanueva, C. Fernández-Lao, L. Díaz-Rodríguez, A. I. Cuesta-Vargas, C. Fernández-de-las-Peñas, B. F. Piper, and M. Arroyo-Morales, "The piper fatigue scale-revised: Translation and psychometric evaluation in spanish-speaking breast cancer survivors," *Qual. Life Res.*, vol. 23, no. 1, pp. 271–276, Feb. 2014.

[37] M. Lozano-Lozano, N. Galiano-Castillo, L. Martín-Martín, N. Pace-Bedetti, C. Fernández-Lao, M. Arroyo-Morales, and I. Cantarero-Villanueva, "Monitoring energy balance in breast cancer survivors using a mobile app: Reliability study," *JMIR mHealth uHealth*, vol. 6, no. 3, p. e67, Mar. 2018.

[38] Y. H. Min, J. W. Lee, Y.-W. Shin, M.-W. Jo, G. Sohn, J.-H. Lee, G. Lee, K. H. Jung, J. Sung, B. S. Ko, J.-H. Yu, H. J. Kim, B. H. Son, and S. H. Ahn, "Daily collection of self-reporting sleep disturbance data via a smartphone app in breast cancer patients receiving chemotherapy: A feasibility study," *J. Med. Internet Res.*, vol. 16, no. 5, p. e135, May 2014.

[39] E. Børøsund, J. Mirkovic, M. M. Clark, S. L. Ehlers, M. A. Andrykowski, A. Bergland, M. Westeng, and L. Solberg Nes, "A stress management app intervention for cancer survivors: Design, development, and usability testing," *JMIR Formative Res.*, vol. 2, no. 2, p. e19, Sep. 2018.

[40] E. Børøsund, C. Varsi, M. M. Clark, S. L. Ehlers, M. A. Andrykowski, H. R. S. Sleveland, A. Bergland, and L. S. Nes, "Pilot testing an app-based stress management intervention for cancer survivors," *Transl. Behav. Med.*, vol. 10, no. 3, pp. 770–780, 2019.

[41] I. Cantarero-Villanueva, "Attenuating cancer treatment-related toxicity in oncology patients with a tailored physical exercise program: Study protocol of the atope trial in women recently diagnosed with breast cancer," Nat. Library Med., ClinicalTrials.gov, Bethesda, MD, USA, Tech. Rep. NCT03787966, Dec. 2018. [Online]. Available: https://clinicaltrials.gov/ct2/show/NCT03787966

[42] T. Saheb and L. Izadi, "Paradigm of IoT big data analytics in the healthcare industry: A review of scientific literature and mapping of research trends," *Telematics Informat.*, vol. 41, pp. 70–85, Aug. 2019.

[43] O. Banos, C. Villalonga, M. Damas, P. Gloesekoetter, H. Pomares, and I. Rojas, "PhysioDroid: Combining wearable health sensors and mobile devices for a ubiquitous, continuous, and personal monitoring," *Sci. World J.*, vol. 2014, Sep. 2014, Art. no. 490824.

[44] O. Banos, M. Amin, W. Khan, T. Ali, M. Afzal, B. Kang, and S. Lee, "Mining minds: An innovative framework for personalized health and wellness support," in *Proc. 9th Int. Conf. Pervas. Comput. Technol. Healthcare*, May 2015, pp. 1–8.

[45] D. Ferreira, V. Kostakos, and A. K. Dey, "AWARE: Mobile context instrumentation framework," *Frontiers ICT*, vol. 2, p. 26, Apr. 2015.

[46] A. Mehrotra, F. Tsapeli, R. Hendley, and M. Musolesi, "MyTraces: Investigating correlation and causation between users' emotional states and mobile phone interaction," *Proc. ACM Interact., Mobile, Wearable Ubiquitous Technol.*, vol. 1, no. 3, pp. 1–21, Sep. 2017.

[47] L. A. Castro, J. Favela, E. Quintana, and M. Perez, "Behavioral data gathering for assessing functional status and health in older adults using mobile phones," *Pers. Ubiquitous Comput.*, vol. 19, no. 2, pp. 379–391, Feb. 2015.

[48] C. Bailon, M. Damas, H. Pomares, D. Sanabria, P. Perakakis, C. Goicoechea, and O. Banos, "Smartphone-based platform for affect monitoring through flexibly managed experience sampling methods," *Sensors*, vol. 19, no. 15, p. 3430, Aug. 2019.

[49] C. A. Low, A. K. Dey, D. Ferreira, T. Kamarck, W. Sun, S. Bae, and A. Doryab, "Estimation of symptom severity during chemotherapy from passively sensed data: Exploratory study," *J. Med. Internet Res.*, vol. 19, no. 12, p. e420, Dec. 2017.

[50] R. Alharthi, R. Alharthi, B. Guthier, and A. El Saddik, "CASP: Context-aware stress prediction system," *Multimedia Tools Appl.*, vol. 78, no. 7, pp. 9011–9031, Apr. 2019.

[51] E. Ferriolli, R. J. E. Skipworth, P. Hendry, A. Scott, J. Stensteth, M. Dahele, L. Wall, C. Greig, M. Fallon, F. Strasser, T. Preston, and K. C. H. Fearon, "Physical activity monitoring: A responsive and meaningful patient-centered outcome for surgery, chemotherapy, or radiotherapy?" *J. Pain Symptom Manage.*, vol. 43, no. 6, pp. 1025–1035, Jun. 2012.

[52] M. D. J. Wolvers, J. B. J. Bussmann, F. Z. Bruggeman-Everts, S. T. Boerema, R. van de Schoot, and M. M. R. Vollenbroek-Hutten, "Physical behavior profiles in chronic cancer-related fatigue," *Int. J. Behav. Med.*, vol. 25, no. 1, pp. 30–37, Feb. 2018.

[53] D. Fuller, E. Colwell, J. Low, K. Orychock, M. A. Tobin, B. Simango, R. Buote, D. Van Heerden, H. Luan, K. Cullen, L. Slade, and N. G. A. Taylor, "Reliability and validity of commercially available wearable devices for measuring steps, energy expenditure, and heart rate: Systematic review," *JMIR Health*, vol. 8, no. 9, Sep. 2020, Art. no. e18694.

[54] S. Moreno, M. Damas, H. Pomares, J. A. Moral-Munoz, and O. Banos, "First approach to automatic performance status evaluation and physical activity recognition in cancer patients," in *Proc. 15th Int. Conf. Ubiquitous Comput. Commun. Int. Symp. Cyberspace Secur. (IUCC-CSS)*, Granada, Spain, Dec. 2016, pp. 116–123.

[55] C. M. Kelly and A. Shahrokni, "From shelf to bedside—Wearable electronic activity monitoring technologies might assist oncologists in functional performance status assessment of older cancer patients," *Clin. Colorectal Cancer*, vol. 16, no. 2, pp. e115–e118, Jun. 2017.

[56] S. Moreno, M. Damas, I. Rojas, V. Amezcua, P. Gutierrez-Pastor, and O. Banos, "Ubiquitous assessment of the recovery of cancer patients using consumer-level activity trackers," *Proceedings*, vol. 2, no. 19, p. 1204, Oct. 2018.

[57] D. Fujisawa, J. S. Temel, J. A. Greer, A. El-Jawahri, L. Traeger, J. M. Jacobs, S. Cutrono, and W. F. Pirl, "Actigraphy as an assessment of performance status in patients with advanced lung cancer," *Palliative Supportive Care*, vol. 17, no. 5, pp. 574–578, 2019.

[58] N. Ohri, R. Kabarriti, W. R. Bodner, K. J. Mehta, V. Shankar, B. Halmos, M. Haigentz, B. Rapkin, C. Guha, S. Kalnicki, and M. Garg, "Continuous activity monitoring during concurrent chemoradiotherapy," *Int. J. Radiat. Oncol. Biol. Phys.*, vol. 97, no. 5, pp. 1061–1065, Apr. 2017.

[59] C. A. Low, D. H. Bovbjerg, S. Ahrendt, M. H. Choudry, M. Holtzman, H. L. Jones, J. F. Pingpank, L. Ramalingam, H. J. Zeh, A. H. Zureikat, and D. L. Bartlett, "Fitbit step counts during inpatient recovery from cancer surgery as a predictor of readmission," *Ann. Behav. Med.*, vol. 52, no. 1, pp. 88–92, Jan. 2018.

[60] D. Xiaosheng, Y. Xiangren, H. Shuyuan, G. Dezong, C. Mengyao, and D. Meng, "The effects of combined exercise intervention based on Internet and social media software for postoperative patients with breast cancer: Study protocol for a randomized controlled trial," *Trials*, vol. 19, no. 1, p. 477, Sep. 2018.

[61] K. E. Uhm, J. S. Yoo, S. H. Chung, J. D. Lee, I. Lee, J. I. Kim, S. K. Lee, S. J. Nam, Y. H. Park, J. Y. Lee, and J. H. Hwang, "Effects of exercise intervention in breast cancer patients: Is mobile health (mHealth) with pedometer more effective than conventional program using brochure?" *Breast Cancer Res. Treat.*, vol. 161, no. 3, pp. 443–452, Feb. 2017.

[62] O. Banos, C. Villalonga, R. Garcia, and A. Saezfor "Design, implementation and validation of a novel open framework for agile development of mobile health applications," *BioMed. Eng. Line*, vol. 14, no. S6, pp. 1–20, Aug. 2015.

[63] O. Banos, M. Bilal Amin, W. Ali Khan, M. Afzal, M. Hussain, B. H. Kang, and S. Lee, "The mining minds digital health and wellness framework," *Biomed. Eng. Line*, vol. 15, no. S1, p. 76, Jul. 2016.

[64] Y. O'Connor, W. Rowan, L. Lynch, and C. Heavin, "Privacy by design: Informed consent and Internet of Things for smart health," *Procedia Comput. Sci.*, vol. 113, pp. 653–658, Dec. 2017.
[65] C. Granja, W. Janssen, and M. A. Johansen, "Factors determining the success and failure of eHealth interventions: Systematic review of the literature," *J. Med. Internet Res.*, vol. 20, no. 5, May 2018, Art. no. e10235.
[66] General Data Protection Regulation (GDPR), "Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing directive 95/46/EC (general data protection regulation)," *Off. J. Eur. Union*, 2016.
[67] A. Javaloyes, J. M. Sarabia, R. P. Lamberts, and M. Moya-Ramon, "Training prescription guided by heart-rate variability in cycling," *Int. J. Sports Physiol. Perform.*, vol. 14, no. 1, pp. 23–32, Jan. 2019.
[68] D. Niederer, L. Vogt, C. Thiel, K. Schmidt, M. Bernhörster, A. Lungwitz, E. Jäger, and W. Banzer, "Exercise effects on HRV in cancer patients," *Int. J. Sports Med.*, vol. 34, no. 01, pp. 68–73, Aug. 2012.
[69] D. J. Plews, P. B. Laursen, Y. L. Meur, C. Hausswirth, A. E. Kilding, and M. Buchheit, "Monitoring training with heart-rate variability: How much compliance is needed for valid assessment?" *Int. J. Sports Physiol. Perform.*, vol. 9, no. 5, pp. 783–790, Sep. 2014.
[70] M. A. Peltola, "Role of editing of RR intervals in the analysis of heart rate variability," *Frontiers Physiol.*, vol. 3, p. 148, May 2012.
[71] D. A. Giles and N. Draper, "Heart rate variability during exercise: A comparison of artefact correction methods," *J. Strength Conditioning Res.*, vol. 32, no. 3, pp. 726–735, Mar. 2018.
[72] Fitbit. (2020). *Fitbit Development: Web API*. Accessed: Jun. 26, 2020. [Online]. Available: https://dev.fitbit.com/build/reference/web-api/
[73] Google. (2020). *Flutter—Beautiful Native Apps in Record Time*. Accessed: Jun. 15, 2020. [Online]. Available: https://flutter.dev/
[74] A. Cutillo, E. O'Hea, S. Person, D. Lessard, T. Harralson, and E. Boudreaux, "NCCN distress thermometer: Cut off points and clinical utility," *Oncol. Nursing Forum*, vol. 44, no. 3, pp. 329–336, May 2017.
[75] AURA and Contributors. (2020). *Aura-Healthcare/Hrvanalysis*. Accessed: Sep. 13, 2020. [Online]. Available: https://github.com/Aura-healthcare/hrvanalysis
[76] ORCAS and Contributors. (May 2013). *Python-Fitbit: Fitbit API Python Client Implementation (version 0.3.1)*. Accessed: Jul. 12, 2019. [Online]. Available: https://github.com/orcasgit/python-fitbit
[77] H. Gehlbach and S. Barge, "Anchoring and Adjusting in Questionnaire Responses," *Appl. Social Psychol.*, vol. 34, no. 5, pp. 417–433, 2012. [Online]. Available: https://dash.harvard.edu/handle/1/11393840
[78] J. Nielsen. (2020). *Deep Linking is Good Linking*. Accessed: Jul. 26, 2020. [Online]. Available: https://www.nngroup.com/articles/deep-linking-is-good-linking/
[79] Apple. (2020). *Universal Links—Apple Developer*. Accessed: Jun. 26, 2020. [Online]. Available: https://developer.apple.com/ios/universal-links/
[80] M. Kamath and E. Fallen, *Correction Heart Rate Variability Signal for Ectopics Missing Beats*, M. Malik and C. A. R. Variability, Eds. Armonk, NY, USA: Futura, 1995.
[81] Docker. (2020). *Docker: Empowering App Development for Developers*. Accessed: Sep. 30, 2020. [Online]. Available: https://www.docker.com/
[82] Unbit. (2020). *The uWSGI Project—uWSGI 2.0 Documentation*. Accessed: Sep. 30, 2020. [Online]. Available: https://uwsgi-docs.readthedocs.io/en/latest/
[83] J. Brooke, *SUS: A Quick and Dirty Usability Scale*, P. W. Jordan, B. Thomas, B. Weerdmeester, and L. McClelland, Eds. London, U.K.: Usability Evaluation in Industry, 1986.
[84] W. C. Adams, "Conducting semi-structured interviews," in *Handbook Practical Program Evaluation*, K. E. Newcomer, H. P. Hatry, and J. S. Wholey, Eds. Hoboken, NJ, USA: Wiley, Oct. 2015, pp. 492–505.
[85] usabiliTEST. (2020). *System Usability Scale Online With Analytics|Usabilitest*. Accessed: Sep. 2, 2020. [Online]. Available: https://www.usabilitest.com/system-usability-scale
[86] J. Yu, W. Ouyang, M. L. K. Chua, and C. Xie, "SARS-CoV-2 Transmission in Patients With Cancer at a Tertiary Care Hospital in Wuhan, China," *JAMA Oncol.*, vol. 6, no. 7, pp. 1108–1110, 2020.
[87] H. O. Al-Shamsi, W. Alhazzani, A. Alhuraiji, E. A. Coomes, R. F. Chemaly, M. Almuhanna, R. A. Wolff, N. K. Ibrahim, M. L. Chua, S. J. Hotte, B. M. Meyers, T. Elfiki, G. Curigliano, C. Eng, A. Grothey, and C. Xie, "A practical approach to the management of cancer patients during the novel coronavirus disease 2019 (COVID-19) pandemic: An international collaborative group," *Oncologist*, vol. 25, no. 6, p. 936, Jun. 2020.
[88] Z. Zhao, A. Arya, R. Orji, and G. Chan, "Physical activity recommendation for exergame player modeling using machine learning approach," in *Proc. IEEE 8th Int. Conf. Serious Games Appl. Health (SeGAH)*, Vancouver, BC, Canada, Aug. 2020, p. 10.

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