



OPEN Fatigue trajectories by wearable remote monitoring of breast cancer patients during radiotherapy

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The aim of this pilot study was to assess the compliance of breast cancer (BC) patients with fitness tracker (FT) monitoring program during radiotherapy (RT) and to characterize radiation-induced fatigue (RIF) status through objective evaluation using FT-collected parameters. Thirty-six BC patients were invited to wear FT during their RT course for continuous monitoring of heart rate (HR) and step counts (STP). RIF assessment was performed weekly, according to CTCAE v5.0 and dichotomized into G0 vs. any-grade. A novel concept based on patient Repeated Activity Window (RAW) was introduced to evaluate HR and STP variations during RT. Several Machine Learning (ML) methods were trained to characterize RIF on the basis of HR and STP collected data. RIF of any grade was reported by 17 out of 36 patients (47%) included in the study. None of patient clinical variables were significantly correlated with RIF. All patients accepted the FT monitoring program, and for 32 patients FT collection efficiency was greater than 60%. For each patient, a distinct distribution of RAWs was identifiable over RT and across the entire patient cohort, with a total of 7950 RAWs processed. Six features related to RAWs, HR and STP were identified as associated with RIF. The best-performing classifier was the Bagged Trees model, showing a cross-validated ROC-AUC of 89% (95% CI 88–90%). This study confirms the feasibility of continuous biomedical monitoring of BC patients by FT. We successfully identify objective indicators of RIF through HR and STP variation measures within each patient's RAW, thus providing a novel and practical approach to assess and manage RIF. This can significantly aid medical staff in evaluating RIF trajectories, potentially leading to better individualized care strategies and improved patient outcomes.

Keywords Fitness tracker, Radiation-induced fatigue, Breast cancer, Quality-of-life

Cancer is a complex disease in which outcome, in addition to its biological behavior and stage, is also influenced by the global performance status (PS) of the patient that is an indicator of prognosis, eligibility for treatment, and patient's quality of life (QoL)^{1–3}. When visiting a cancer patient, a performance score is assigned⁴, which is based on possible comorbidities, their autonomy in daily life activities, and their treatment needs. This score takes into account factors such as the frequency of care required, the assistance needed for self-care, and any limitations in daily activity. However, the two available systems for defining PS often prove to be too subjective, which can lead to incorrect therapeutic choices⁵. Hence, it might be beneficial to integrate an objective assessment of activity to enhance the evaluation of PS.

Breast cancer (BC) patients represent a long-term survivor group, and the impact of the therapy on their QoL is significant⁶. Radiotherapy (RT) is generally well tolerated⁷, however, radiation-induced fatigue (RIF) is a frequent side effect reported by patients that can reduce activity and affect QoL⁸.

It is widely recognized that moderate physical activity improves the QoL of cancer patients through various interconnected mechanisms. These include improved insulin sensitivity with consequent reduction in blood sugar levels, a positive impact on sleep quality, decreased levels of fat tissue (resulting in reduced production of

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pro-inflammatory cytokines), increased muscle mass and strength (leading to decreased fatigue), and a positive impact on mood through the release of endorphins⁹.

Several Bluetooth Low Energy Fitness Activity Trackers (FT)^{10–12} are available on the market, which are capable of detecting parameters such as steps per minute, sleep level, blood pressure, heart rate, blood oxygen saturation^{13–15}. While these devices were not originally designed for medical purposes, they have the potential to aid in remote monitoring, requiring minimal compliance, and providing objective health information¹⁶. However, to fully exploit the capabilities of such wireless body sensors, appropriate development frameworks, methodologies, techniques, and implementation tools are required for effectively support this growing technology in a clinical setting^{17–20}.

The objective of the current pilot study was to introduce a new methodology for BC patients monitoring using FT during their RT course. This aimed to: (i) determine the feasibility and patient compliance with the FT monitoring program during RT, (ii) analyze patient activity trajectories using biomedical data gathered from FT devices, and (iii) identify the most appropriate FT-collected data able to provide an objective assessment of RIF, thereby enhancing the accuracy of therapeutic decisions and improving patient care.

Materials and methods

Patients and data collection

A total of 36 BC patients undergoing RT at Federico II University Hospital in Naples, Italy, were invited to participate in a monitoring protocol by wearing an FT device during RT and instructed to wear them throughout the entire day. All participants signed informed consent and the patient data were analyzed anonymously. This study was approved by the local Ethics Committee (Comitato Etico per le Attività Biomediche, Università Federico II, Napoli, protocol code n. 222-10, 9th March 2017). All experimental protocols and procedures were performed in accordance with the guidelines of the Federico II University of Naples.

Patients received moderately hypofractionated or conventional RT fractionation schedule, depending on whether the target volume included the chest wall and/or elective nodes. All fractionation schedules consisted of one fraction a day, five fractions a week. The treatment duration was 3–5 weeks. Patient and treatment related characteristics were collected. Treatment-related toxicity assessment, including RIF, was performed weekly according to CTCAE version 5.0. For subsequent data analysis, RIF was dichotomized into G0 and any-grade (G1–G2).

Fitness activity trackers

The FT devices (Veepoo H03 smart watch) served as wearable sensors for gathering biomedical data such as step counts (STP), heart rate (HR), sleep level and oxygen saturation. The primary endpoint of the present study was the collection of STP and HR parameters with the aim of characterizing variations in patient habits during RT. In Supplementary Material Table S1, the sampling rates for the STP and HR set by the manufacturer were reported.

The battery life of FT devices lasted approximately 3 days. For this reason, patients were asked to replace their device every 2 days with a new one fully charged.

The used devices were capable of monitoring patient data independently, without the need for a smartphone or internet connection, as they utilized internal memory to store the collected data. In addition, these devices do not require any patient interaction. A gateway located in the RT department^{21,22}, collected the data stored in the memory of the FT as soon as the patient entered the waiting room.

No patient personal information was stored in the device according to General Data Protection Regulation (GDPR) recommendations. A dedicated in-house application hosted on the gateway and developed for the needed tasks²³ pre-processed the anonymized data and sent to the hospital server. Data were available to the medical staff throughout the therapy course thanks to a web application²¹ specifically designed for the use case scenario. Briefly, the patient was invited by the medical staff to wear the FT continuously during domestic/outside activities and during rest. Upon arrival at the RT department, the data were downloaded from the FT memory to the gateway. Data aggregation by patients and activities were made available to the medical staff in the form of graphs. The doctor integrated this information with that from the clinical interview (clinical visit, administration of questionnaires). The patient left the hospital and the process repeated for all the radiation treatment course (Fig. 1a).

The acceptance rate of the FT monitoring protocol was defined as the ratio of participants to the total number of patients to whom FT was proposed.

A collection efficiency was introduced as the ratio of HR collected and HR collectible during RT time, considering the device's acquisition performance. Compliance rate was accordingly defined as the ratio of patients who wore FT from the beginning to the end of RT with a collection efficiency greater than 60% to the total patients wearing the FT.

Data extraction

FT data extraction process consisted of two distinct phases.

In a first phase, the data collected from FT were preprocessed to standardize the data sampling frequency. STP and HR were, by design, characterized by a different sampling rate, necessitating sampling synchronization for further processing. In the preprocessing step, data gaps (occasionally missing observations²⁴) were also removed.

In a subsequent phase, it was necessary to define patient “activity windows”. Each patient is indeed characterized by her own habits, which determine various activity windows throughout the 24-h day^{25,26}. To recognize and characterize the repeated activity windows (RAWs) that recur throughout the RT duration, we designed a dedicated algorithm²⁷ developed in MATLAB® (MathWorks, Natick, MA) and described in detail in Appendix 1. In such defined RAWs, it was possible to effectively evaluate FT biomedical parameters (Fig. 1b,c).

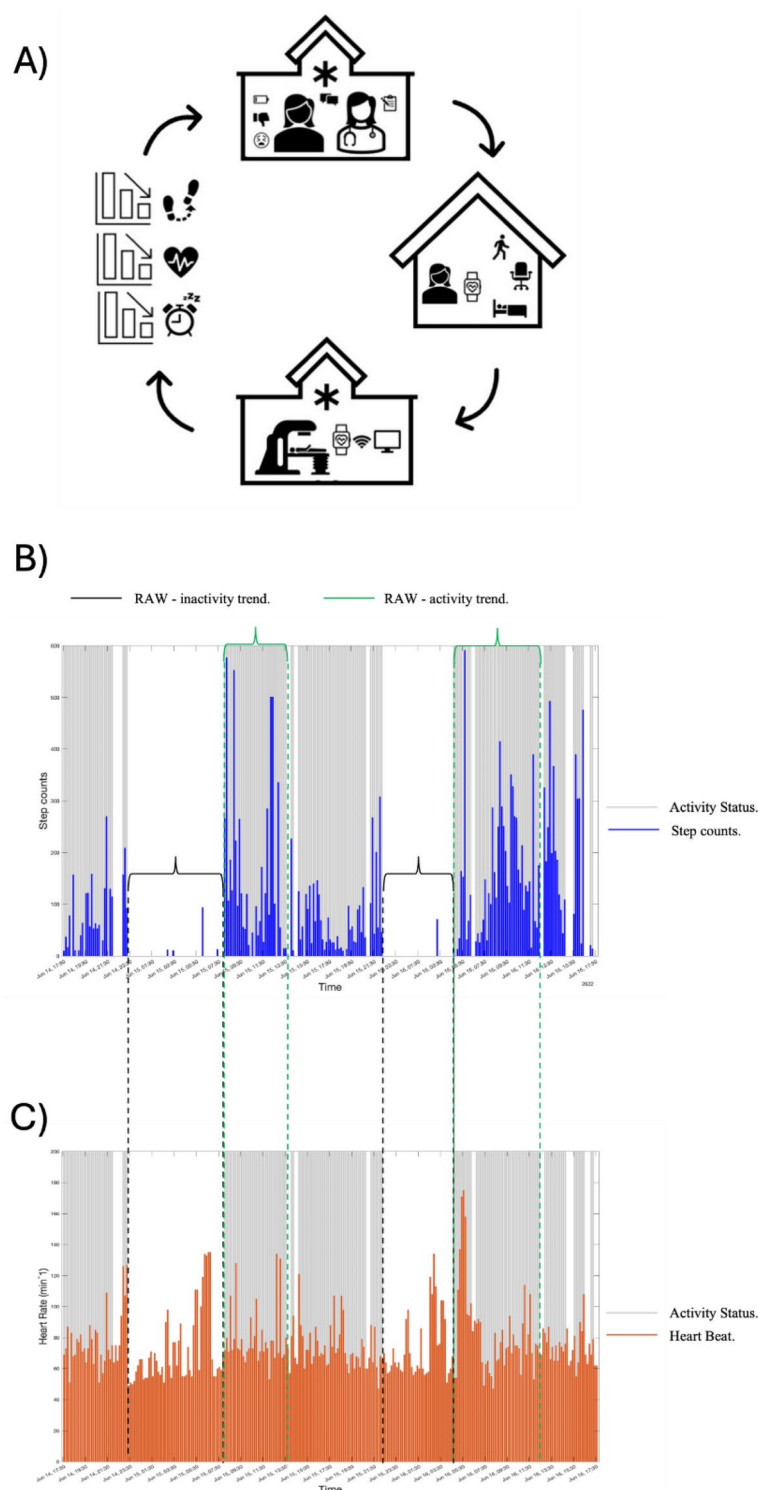


Fig. 1. (A) Workflow of data collection by fitness tracker (FT) throughout the radiation therapy course. (B) Step counts (STP) and activity status data extraction during two days. Two Repeated Activity Windows (RAWs) on two consecutive days are marked in green (active trend) and red (inactive trend). They may refer to possible patient habits. (C) Heart Rate data extraction in the same time span as showed in (B).

In particular, for each patient, it was possible to identify HR and STP variations within their RAWs and the following features were accordingly identified: start timestamp, end timestamp, duration, RAW start time, RT day, activity status (1 vs. 0), STP mean, HR mean, STP sum, HR sum, STP standard deviation, HR standard deviation, mean $\Delta\text{STP}/\Delta\text{Timestamp}$. A detailed description of each feature is provided in Table 1.

	RAW features	Description
1	Start timestamp	The time at which the RAW starts (format: yyyy:mm:dd hh:mm:ss)
2	End timestamp	The time at which the RAW ends (format: yyyy:mm:dd hh:mm:ss)
3	Duration	The duration of RAW in seconds
	RAW start time	The time of day (00:24) at which the RAW starts
5	RT day	The number of days between the start of the RT and the start of RAW
6	HR sum	The sum of the HR in a RAW
7	STP sum	The sum of the STP counts in a RAW
8	HR standard deviation (SD)	The standard deviation of HR in a RAW
9	STP standard deviation (SD)	The standard deviation of STP in a RAW
10	HR mean	The mean of the HR sampled between two consecutive timestamps in a RAW
11	STP mean	The mean of the STP sampled between two consecutive timestamps in a RAW
12	Mean Δ STP/ Δ Timestamp	The mean patient speed registered in a RAW calculated as mean of $[\text{STP}(i+1) - \text{STP}(i)] / [\text{timestamp}(i+1) - \text{timestamp}(i)]$ with i timestamp index in a RAW
13	Activity status	Binary value associated to activity (1) and inactivity (0) windows

Table 1. Description of the extracted repeated activity window (RAW) related features. *HR* Heart rate, *STP* Step counts.

Statistical analysis

Patient, disease and treatment-related characteristics were examined according to the development of RIF. Categorical variables were expressed as percentages and tested by Pearson's χ^2 -test or Fisher's exact test when appropriate; the median and the range were used to describe all continuous variables and Mann–Whitney U-test was employed for analyzing them.

Subsequently, to identify possible association between the RAW features described in Table 1 and RIF, data of participants who were fully compliant to FT monitoring program were randomly divided in two sets: a training dataset and a test dataset, maintaining a 5:1 ratio. Fine Tree Machine Learning (ML) algorithm²⁴ was used to identify candidate RIF associated features, including possible nuisance clinical variables significantly correlated with RIF. Feature selection was then performed using an ANOVA-based feature ranking algorithm²⁸, with a threshold set at a value of 3 for the importance score, taking into account the population size. Following variable selection, we tested four commonly used classification methods in ML: Fine Tree, Bagged Trees, Neural Network, K-Nearest Neighbors (KNN)^{29,30}. By comparing the performance of these different algorithms, we aimed to identify the most effective model for characterizing RIF based on the selected features.

Each model's performance was assessed on the training data using fivefold cross-validation to ensure robustness and to mitigate overfitting. The methods were trained by Classification Learner available in MATLAB 2023b.

The Fine Tree algorithm was set with the fine tree preset, a maximum of 140 splits, and the maximum deviance reduction as split criterion. The Ensemble algorithm was set with a Bag preset, 279 learners and a maximum of 6122 splits. The Neural Network algorithm was set with 3 fully connected layers, each layer having a size of 10. The KNN algorithm was set with the coarse KNN preset with 100 neighbors, a Euclidean distance metric, and equal distance weighting. The test dataset was used to assess the predictive capability of the trained models. The classification performance of the models was evaluated by accuracies from both train and test dataset, and Receiver Operating Characteristics (ROC)–Area Under the Curve (AUC) (train and test dataset).

Results

Study population

All 36 patients had a good performance score. RIF was reported by 17 out of 36 patients (47%). Patient clinical and treatment characteristics were described in Table 2. At univariable analysis, none of the patient clinical variables was significantly correlated with RIF.

An overview of RIF experienced by patients during RT is provided in Supplementary Material, Table S2. Of note, all patients except one (97%) experienced dermatitis, mostly G1; 12 patients (33%) experienced G2 dermatitis.

FT compliance

All patients accepted to participate in the monitoring program (100% acceptance rate). One patient wore the device continuously but only for the first RT week, reporting discomfort after a certain period and she was accordingly excluded from further analysis.

Three patients wore the FT for the entire treatment duration, though not continuously and the data collection efficiency resulted to be less than 60%. For 32 patients the FT data collection efficiency was over the set threshold of 60%. Accordingly, the final compliance rate was 89%.

Clinical and treatment feature	All (n = 36)	Fatigue		p-value
		G0 (n = 19)	Any-grade (n = 17)	
Age	55.5 (31–72)	56 (31–72)	55 (39–68)	0.802
KPS (%)				
90	15 (42%)	6 (32%)	9 (53%)	0.285
100	21 (58%)	13 (68%)	8 (47%)	
BMI	26.6 (21.5–39.5)	26.6 (22.5–39.5)	26.5 (21.5–37.4)	1
Normal	15 (42%)	7 (37%)	8 (47%)	0.738
Overweight or obese	21 (58%)	12 (63%)	9 (53%)	
Smoke				
Current/former	7 (19%)	5 (26%)	2 (12%)	0.408
Heart comorbidity	15 (78%)	8 (16%)	7 (41%)	0.736
Surgery				
Conservative	28 (78%)	17 (89%)	11 (64%)	0.114
Radical	8 (22%)	2 (11%)	6 (35%)	
Histotype				
Ductal	13 (36%)	6 (32%)	7 (41%)	0.73
Lobular	4 (11%)	2 (11%)	2 (12%)	1
NST	16 (44%)	9 (47%)	7 (41%)	0.749
NR	3 (11%)			
Stage				
0–1	16 (44%)	8 (42%)	11 (64%)	0.202
2–3	20 (56%)	11 (58%)	16 (94%)	
Adjuvant CHT	5 (14%)	4 (21%)	1 (6%)	0.187
Neoadjuvant CHT	9 (25%)	4 (21%)	5 (29%)	0.706
Target therapy	6 (11%)	1 (5%)	5 (29%)	0.081
Endocrine therapy	33 (92%)	17 (89%)	16 (94%)	0.543
IHC				
Luminal	29 (81%)	16 (84%)	3 (18%)	0.402
HER2+	4 (11%)	0 (0%)	4 (24%)	0.050
Triple negative	2 (6%)	2 (6%)	0 (0%)	0.486
Target				
Breast	32 (89%)	18 (95%)	14 (82%)	0.326
Chestwall	4 (11%)	1 (5%)	3 (18%)	0.326
N	10 (28%)	3 (16%)	7 (41%)	0.139
Laterality				
Right	14 (39%)	8 (42%)	6 (35%)	0.742
Left	22 (61%)	11 (58%)	11 (64%)	1
Bilateral	1 (3%)	1 (5%)	0 (0%)	1
Dmax prescription dose BED ₄ (Gy)	83 (66.8–90.6)	83 (66.8–90.6)	83 (75–90.6)	0.433

Table 2. Clinical and treatment characteristics of the whole, study population, and according to fatigue, with statistics. *KPS* Karnofsky Performance Score, *BMI* Body Mass Index, *IHC* Immunohistochemistry, *N* Nodes.

Repeated activity windows

For each patient, a distinct distribution of RAWs was identifiable over the course of RT treatment days. Across the entire patient cohort, a total of 7950 RAWs were collected. The mean values of RAWs related features for the whole cohort and according to RIF development were reported in Supplementary Material Table S3.

The dataset of RAWs was split into a training set (6315 RAWs, 25 patients) and a test set (1635 RAWs, 7 patients). Eleven features were selected by Fine Tree as candidate features while 6 were identified as associated with RIF, based on their ANOVA-derived importance score (Fig. 2). These features include start timestamp, RAW start time, HR mean, HR standard deviation, STP standard deviation, mean Δ STP/ Δ Timestamp.

All tested ML models demonstrated moderate to good predictive performance for RIF (Table 3 and Fig. 3), with accuracies ranging from 70 to 80% in the training set. Confusion matrices for all models are reported in Supplementary Material Fig. S1.

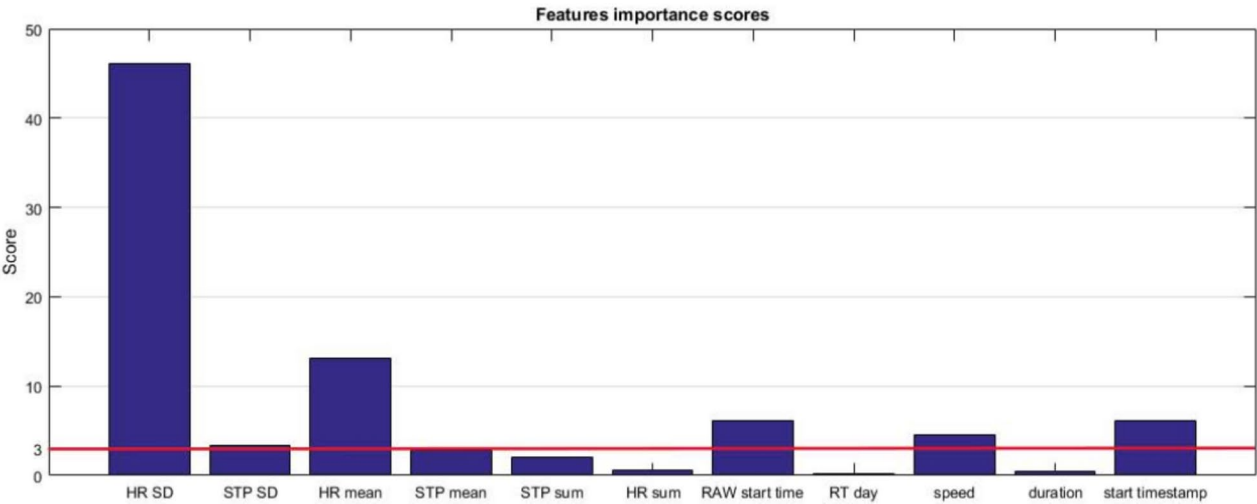


Fig. 2. Feature importance scores selected by Analysis of Variance (ANOVA) algorithm. The red dashed-line indicates an importance score of 3; 6 features have an importance score major or equal to 3.

Performance	Bagged tree	Fine tree	Neural network	KNN
Accuracy (training)	80%	77%	76%	70%
Total cost (training)	1286	1452	1531	1987
Accuracy (test)	85%	86%	73%	72%
Total cost (test)	268	175	449	496
Time (s)	255	25	15	2
AUC (training)	89%	86%	86%	76%
95% CI (training)	(89–90)%	(85–87)%	(85–86)%	(74–77)%
AUC (test)	86%	93%	86%	55%

Table 3. Performance measures for each machine learning model.

Discussion

The pandemic era has introduced significant changes in healthcare, marked by the implementation of telemedicine and remote monitoring. The interest in the use of non-medical tracking devices for medical purposes is, therefore, growing³¹. While it is not yet well known how FT can play their role, various studies have analyzed adherence to remote tracking, sleep and activity levels among oncological patients. Monitored physical activity seems to correlate with clinician assessed performance status¹¹ and possibly with toxicity in cancer patients: step counts per day could serve as an adjunct to performance status assessment and a possible help to identify vulnerable populations³². Various studies have focused their attention on the role of physical activity during preoperative treatments. In pancreatic cancer patients, moderate exercise can reduce surgical complications and accelerate recovery from surgery³³. During chemotherapy for breast cancer, patients typically experience a decrease in physical activity. Adherence to interventions aimed at reversing this trend appears to be higher among younger patients and receiving adjuvant chemotherapy³⁴. If several studies have explored biomedical monitoring before, during or after chemotherapy or surgery¹⁹ there is a paucity of research^{35–38} regarding the monitoring of cancer patients during their RT course (Supplementary Material Table S4). The preliminary results of a pilot study by Sher et al.³⁸ about wearable activity monitoring during RT for a large sample of head and neck malignancies, have been recently published. Although not meeting the compliance goal, most patients did use the wearable device; their signal could not identify patients requiring hospitalization or significantly more pain medication, but the finding of reduced STP before a significant reduction in quality of life was suggestive. Association between biomedical parameters and QoL had already described by Lowe et al.³⁵, showing that, in a sample of patients bearing brain metastases undergoing palliative whole brain RT, sedentary behavior was associated with better physical functioning but with worse psychosocial functioning. The study was limited by malfunctioning of accelerometers. Moreover, those patients are characterized by a low level of physical activity since baseline which can hardly be increased. Ohri et al.³⁶ have more concretely demonstrated the possibility to identify vulnerable patients during RT; performing continuous activity monitoring during concurrent chemoradiotherapy on 38 patients with different primaries, a significant association was found between recent step counts and hospitalization risk.

Notably, BC is a more common malignancy, and BC patients represent a better-prognosis group with long-term survivors. One of the main side effects related to RT is fatigue, although it is not completely clear how it

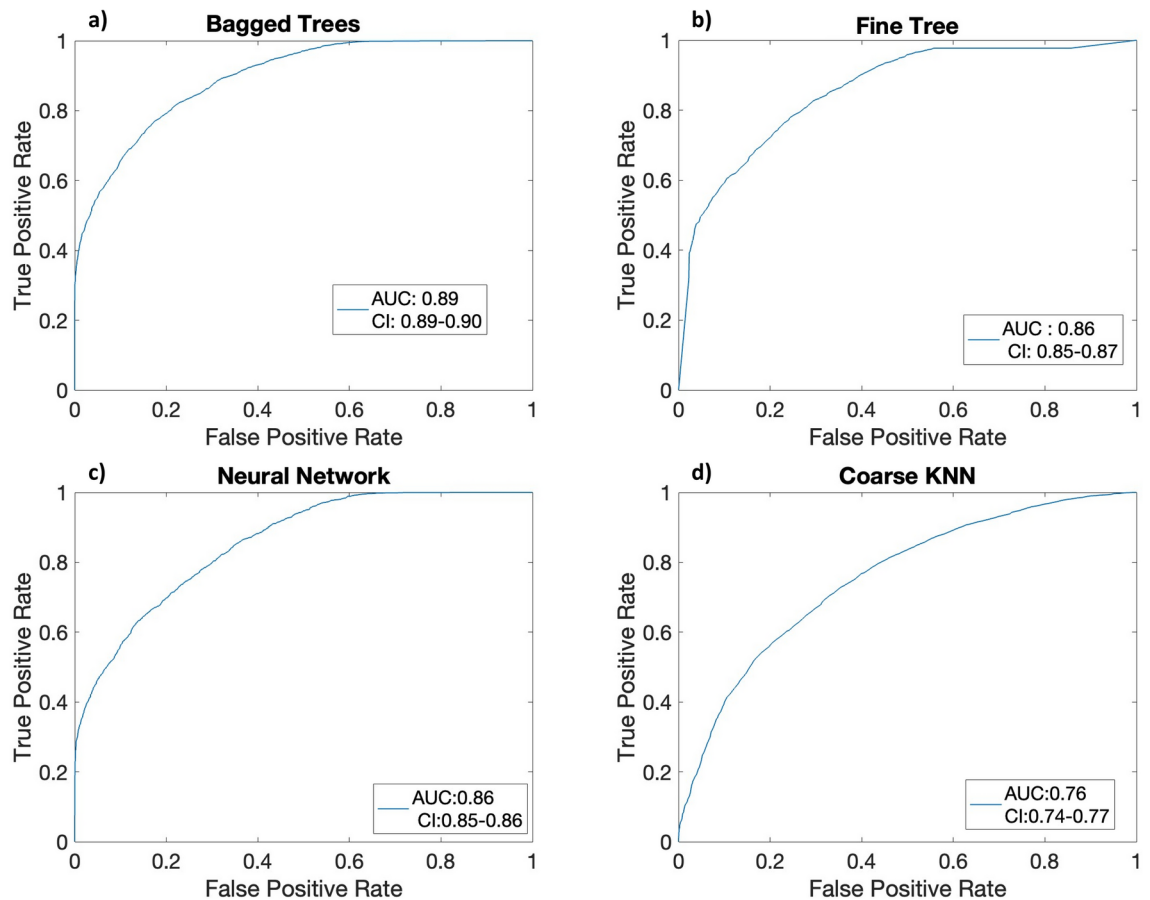


Fig. 3. Model ROC curves on the training dataset: bagged trees model (a), fine tree model (b), neural network model (c), K-nearest neighbors model (d).

impacts on physical activity. Champ et al.³⁷ selecting ten patients, found transient changes in activity levels during RT. Despite its limitation -above all, the small sample size- they identified the path of RT as an opportune time to start implementing changes prior to survivorship for BC patients.

The present study represents a pilot, primarily aimed at assessing the compliance of BC patients in continuously wearing FT during 3–5 weeks of RT. Our primary goal was to characterize RIF trajectories using objective data collected by these wearable devices. To achieve this, we identified time windows for observing patients' daily habits by introducing RAWs and the related features, including HR and STP variations. Champ et al.³⁷ in their study indeed highlighted significant variability in activity levels among women undergoing RT. This inter-patient variability, potentially due to differing daily habits, prompted us to adopt a novel approach based on the innovative concept of RAWs, allowing us to effectively evaluate HR and STP variations during RT. This approach enabled us to define a kind of fingerprint of each patient activity level.

As expected, BC patients undergoing adjuvant RT proved to be highly compliant. While all patients agreed to wear the FT, continuous monitoring was inadequate for 11% of patients due to interruptions or discontinuities in data collection caused by patient tolerance levels in wearing the device. In addition to patient tolerance, we also considered data collection efficiency to ensure the quality of the collected data, which was directly related to the device's acquisition performance. The FT's acquisition performance was potentially affected by two key factors: (a) limited battery life, leading to interruptions and data gaps in each patient's dataset, and (b) improper or inconsistent use of the device by the patient, causing a loss of information about daily activities. Despite these challenges, only 9% of patients had data collection efficiency below the set threshold.

Various ML algorithms were then tested to capture patterns in the collected FT data that translate these features into an objective description of RIF. The ML algorithms that have been utilized in this study are Fine Tree, Bagged Trees, Neural Network, and KNN which have helped us achieve the results presented in the paper. These algorithms were chosen for their diverse approaches to classification and their proven effectiveness in different contexts. Fine Tree and Bagged Trees represent decision tree-based models, with Fine Tree offering a simple and interpretable model, while Bagged Trees enhance robustness by reducing overfitting through ensemble learning. Neural Networks are powerful in capturing complex, non-linear relationships in data, although they may require significant computational resources and risk overfitting with small datasets. K-Nearest Neighbors (KNN) is an instance-based method known for its simplicity and effectiveness in low-dimensional spaces, but it can struggle

with high-dimensional data and large datasets due to increased computational complexity. By comparing these methods, we aimed to balance model complexity, interpretability, and predictive accuracy.

Notably, the Bagged Trees model exhibited the highest performance, achieving a training-AUC of 89% (95% CI 88–90%) and test-AUC of 86%, while the worst performance was observed with KNN model achieving a training-AUC of 76% (95% CI 74–77%) and a test-AUC of 55% (Fig. 3).

A subset of the extracted RAW features resulted to be important in the description of the RIF status. Specifically, the instants at which the RAWs start provide us with information about the general patterns of patients' activities, enabling intra-patient analysis. Differently, the time of the day at which the RAW starts provides us with information about the daily patient habits, allowing for inter-patient analysis. As regard to STP and HR within RAWs, the standard deviations of step counts and heart rates give a description of the variation in intra-RAW fatigue. The mean HR and mean speed are instead indicative of the variation in patient activity assessable between RAWs.

The supervised learning method suggested that the objective data collected by FT could be useful to define RIF status in patients undergoing RT. Thanks to its sensitivity and specificity, the bagged trees showed to be a powerful tool to characterize RIF over RT time, basing on data collected.

Among the limitations of our study, technical issues related to the chosen FT devices stand out, including the above-mentioned low battery life. Out of the box, the FT's battery lasted about a week, but after several charge/discharge cycles, it only lasted three days. This may be due to the manufacturer using lower-grade components for the batteries. The short battery life hindered baseline and post-discharge data acquisition, limiting data collection efficiency. This was due to the decision not to require patients to recharge their FTs independently, aiming to maintain the study's non-invasiveness. Another contributing factor to the short battery life was the non-configurable sampling frequency. While lowering the heart rate (HR) sampling rate could have extended battery life, it might have resulted in information loss. Additionally, the most significant technical limitation affecting the proposed methodology was the limited memory capacity of the FTs. These devices could only store data from the current day and the previous two days, meaning patients returning to the RT department on a Monday, after weekend treatment break, would have their Friday data lost. To address these challenges, one of the biggest design hurdles involved developing a fully reliable gateway application to collect data from the FTs. The application must efficiently manage multiple FTs in cases where several monitored patients were in the RT waiting room simultaneously, as well as handle retries for unsuccessful downloads due to patients moving in and out of the gateway's range. This process was made more complex by the slow transmission rate of Bluetooth Low Energy, which extended the time needed to download data from FT memory.

Additionally, the small number of enrolled patients may have impacted method performance, as evidenced by the fine tree model performance reported in Table 3. However, to our knowledge, this study represents the first experience in monitored biomedical data analysis among cancer patients using the methodological approach based on RAWs.

The promising preliminary results encourage us to continue enrolling more patients to extend and validate our findings. Our study indeed prospectively opens up several potential clinical applications. Specifically, we have demonstrated that a highly subjective symptom like fatigue can be predicted with reasonable accuracy using wearable devices. This finding offers a model that supports the broader implementation of remote monitoring for cancer patients. The reduction in hospital visits not only addresses the immediate needs brought on by the pandemic but also reflects a growing demand for more accessible healthcare. This shift holds potential benefits across various aspects, including improved patient quality of life, mobility, sustainability, hospital efficiency, and cost-effectiveness.

Conclusions

While remote monitoring in cancer patients is not a novel concept, our experience stands out as one of the few instances observed among BC patients undergoing RT. Our findings highlight BC patients as a particularly compliant group for continuous biomedical monitoring. By FT monitoring of HR and STP within patient's activity windows, healthcare providers may be helped in performing an evaluation of RIF trajectories based on objective data. Investigating the long-term impact of remote monitoring on patient outcomes—such as quality of life, treatment adherence, and survival rates—could provide valuable insights into the clinical utility of these technologies. By validating these approaches in larger trials, remote monitoring could become a standard component of cancer care, enhancing patient autonomy while reducing the burden on healthcare systems.

Data availability

The datasets used and/or analyzed during the current study available from the corresponding authors on reasonable request.

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Author contributions

A.B. and C.F. wrote the main manuscript text and analyzed data. C.F., M.C., A.T. and O.T. implemented the software. M.C., A.F.M.P., C.O., S.C., M.A.A. followed the patients and data curation. R.P., M.C., A.T., M.C. and L.C. conceptualization, review and editing. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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