mEnergy: Development of a Novel mHealth Multi-device Platform for Near Real-time Remote Assessment of Energy Disorders

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***Abstract*— We present the development, architecture, and features of a new multi-device mHealth software platform to support near real-time remote monitoring of metabolic health and timely intervention in the treatment and survivorship of cancer patients. Our platform, mEnergy, leverages a human-centered design process, and integrates in a unified, web-based framework consumer-grade hardware—Fitbit wearable sensor devices, smartphones, and Withings smart scales. mEnergy can aid oncologists in identifying early indicators of muscle-wasting (sarcopenia) due to sleep disturbance, insufficient weight recovery, or reduced/limited activity. The platform aims for a smooth transition into clinical practice and increased adherence to evidence-based recommendations, in particular in underserved geographical areas. This toxicity-surveillance approach based on mHealth technologies can improve treatment outcomes, quality of life, and survivorship.**

I. INTRODUCTION

Smart devices for mobile health (mHealth) offer unprecedented opportunities for remote and distributed toxicity monitoring and timely intervention across health conditions [1]–[3]. Such devices have great potential for medical applications in the context of reduced point of care access, e.g., in rural areas, or when toxicities evolve faster than follow-up care intervals, e.g., rapid loss of muscular mass in cancer treatment. These smart devices can also have complementary strengths: for example, in monitoring metabolic health, smartwatches could detect breathing disturbances, while smart scales could track trends over time in body composition. At the same time, the production and availability of health smart devices are subject to vendor fluctuations. For example, Fitbit currently offers competitive smartwatches but has discontinued its smart scale product, an area in which Withings is now a leader.

Unfortunately, integrating these hybrid health manufacturers and device measurements into a single interface for the purpose of remote surveillance and analysis by clinicians poses significant challenges. These challenges include device reliability and affordability issues, system-level design issues, and analysis and presentation issues. In terms of *device reliability and affordability*, relatively low-cost devices from Fitbit and Withings can reliably detect sleep-related disturbances [4], [5], or body composition fluctuations over time [6], [7], but have yet to be successfully validated in the detection of specific medical conditions. Other mHealth devices have been approved for the detection of specific medical conditions (e.g., Apple watch [8] or Samsung Galaxy watch [9] for apnea detection), but can be cost-prohibitive to underserved patients or points of care [10]. Clinicians and patients should be able to select the set of devices most compatible with their constraints, and leverage their potential integration through open authorization standards like OAuth 2.0, which enable applications to securely access the user data. *System design issues* include accessing, harmonizing and integrating data from these multiple mHealth sources. Internet of Things (IoT) hubs [11] have been introduced in the context of smart homes, where correlations among measurements or devices are less important than in mHealth, and varying data granularity and type are less of a challenge. In the style of these IoT hubs, mHealth applications typically leverage a single device type [1], [12], proprietary dashboards for multiple devices made by the same manufacturer [13], [14], a collection of one app per device manufacturer [15], or construct their own integrated device with multiple sensors [16]. In these approaches, it is difficult to jointly interpret multiple possibly correlated health biomarkers, where different factors measured by different devices are in play. Last, the *analysis and presentation* of these integrated mHealth data through graphical user interfaces or dashboards needs to handle both (a) large amounts of data at multiple granularities, leading to information-dense displays, and (b) an audience with traditionally low data visualization literacy.

In this work, we demonstrate a unified web-based framework for the integration of consumer-grade smart devices from different manufacturers into a patient-specific, cross-platform ecosystem. We instantiate this framework into an interactive system designed to help radiation oncologists remotely monitor the metabolic health of head and neck cancer survivors [17], with a focus on adaptive sleep disturbance, weight recovery, and activity management. Sarcopenia, or muscle wasting [18], [19], which is directly associated with increased mortality and poorer clinical outcomes [20], affects 65% of head and neck cancer patients after radiotherapy and is directly related to survival outcomes across multiple datasets [21], [22], as well as correlated with multi-valent consequential toxicity profiles [23]. While the mechanisms responsible for sarcopenia are not elucidated [24], [25], clinicians could prospectively assess and refer the patients, if appropriate, to the appropriate remote intervention, all included in the current standard of care: (1) referral for home polysomnography (PSG) assessment for sarcopenia due to

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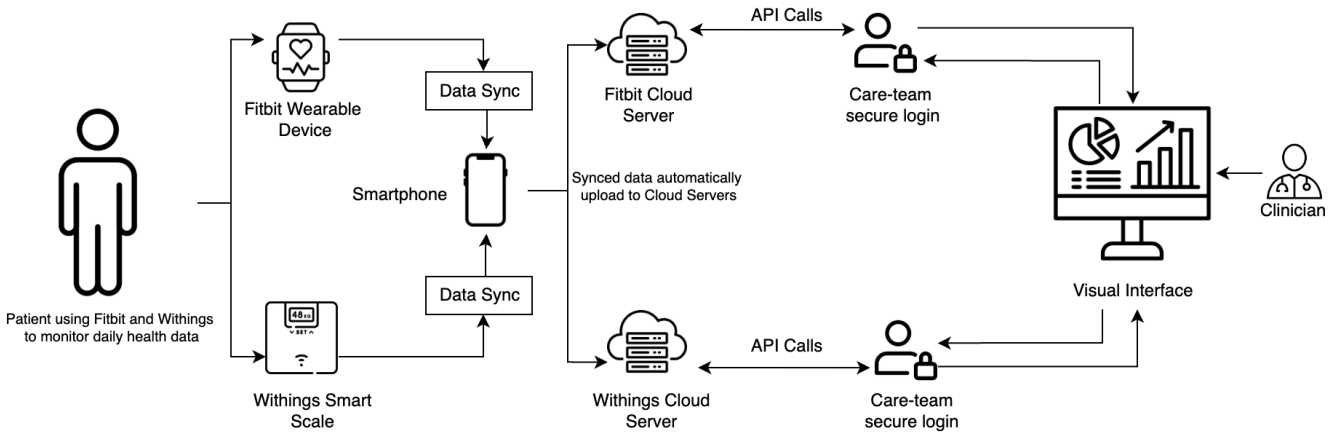

Fig. 1: System Architecture. As part of a clinical study, patients are provided with a Fitbit smartwatch and a Withings smart scale, with credentials issued by their care team, to track daily health data at home. The data is synchronized with the respective cloud servers via the patient smartphone. The care team can then access the data remotely through the platform interface. The interface uses the issued login credentials to gain access, then makes application programming interface (API) calls to retrieve and visualize the data.

sleep disturbance [26]–[28], (2) tele-nutrition consultation for sarcopenia due to insufficient weight recovery, (3) home health/rehab referral for sarcopenia due to reduced/limited activity.

Sarcopenia detection is traditionally performed through evaluation of computed tomography (CT), magnetic resonance imaging (MRI), or dual x-ray absorptiometry (DEXA) imaging results when already being taken for other diagnostic purposes [29], as traditional height-weight formulas have been shown ineffective at discriminating post-therapy muscle loss [30]. However, this method does not allow continuous monitoring during treatment, as these scans are generally done at infrequent intervals. Other approaches include bioelectrical impedance (BIA) [31], ultrasound, hand-grip strength, and measurements of deuterated creatine in urine. Of these approaches, BIA has been shown to be comparable to CT scans [31] and hand-grip strength [32], and is uniquely available in commercial home-monitoring devices. Our framework instantiation demonstrates integration of consumer-grade devices: a BIA smart scale (Withings Body+) with a smartwatch that measures peripheral capillary hemoglobin oxygen saturation (SpO2) via photoplethysmography (Fitbit Sense 2), which serves as a proxy for respiration and can identify hypopneic events during sleep.

II. Methods

This work reflects an interdisciplinary remote collaboration among three research teams. The core teams consisted of radiation head and neck oncologists at the MD Anderson Cancer Center at the University of Texas, a data mining expert at the University of Iowa, and human-centered data scientists at the University of Illinois Chicago (UIC). The team met weekly to identify project goals, and to discuss progress in the data collection, authentication, and the system's design. Because our approach leverages consumer-grade hardware on the patient side, and the platform is to be used by clinicians only, our design process did not include patient input. We adopted an Activity-Centered Design (ACD) approach [33], an extension of Human-Centered Design, due to its higher success rate in interdisciplinary collaboration settings. The UIC Institutional Review Board approved all experimental procedures involving human subjects in this work.

Requirements for our system were identified through interviews with our clinical collaborators and refined through feedback in regular meetings where designs and system prototypes were shared with the team. The following requirements related to sarcopenia risk were identified: (1) Monitor insufficient weight recovery during treatment and after through body composition trends over 3-12 months; (2) Monitor sleep disturbance by evaluating indicators of apnea such as night-time SpO2, heart rate and sleep quality over time; (3) Monitor reduced or limited activity; (4) Support analysis of correlation among these factors, including patient reported outcomes (PROs) that could help differentiate between apnea, sarcopenia, and chemo-radiation effects: fatigue, sleep quality, pain, and drowsiness [34]–[37].

Non-functional requirements included visual scalability and a low learning curve [38], 24/7 remote accessibility, and secure access to the patient data.

A. Data, Processing, and Implementation

Our framework integrates data generated by a subject via PROs, a Fitbit Sense 2 smartwatch and a Withings Body+ scale. The devices generate daily readings of weight, muscle mass, fat mass, and bone mass over time (Withings Body+), respectively daily ratings of sleep efficiency scores, total time spent in each sleep stage, minutes spent at each activity level, daily calories burned, and steps over time, as well as intraday oxygen saturation, intraday heart rate and sleep stages during sleep at minute intervals (Fitbit Sense 2). The data includes demographic and clinical information such as gender, age,

Fig. 2: Visual analysis of multi-device health data. (A) Demographics and PRO information panel showing demographics and patient-reported outcomes (B) Navigation panel to view data on a yearly, quarterly, monthly, or weekly basis as well as a custom range. (C) Body composition panel: (C.1) Sarcopenic trend over time. (C.2) Muscle mass ratio and fat mass ratio trends for the selected month, with the option to track weight trends. The panel indicates that the subject has a healthy body composition pattern and no significant muscle loss. (D) Sleep Analysis Panel: (D.1) Sleep quality showing the overall sleep quality score for the selected time period. (D.2) SpO2/HR view showing oxygen saturation level (SpO2), with red indicating possible sleep disturbance events and heart rates (HR) in black during a selected day/night, and dotted horizontal lines showing average daily SpO2 and HR. The color-coded background reflects different sleep stages. The subject is experiencing multiple sleep disturbance events, a potential indication of apnea events. (E) Activity Panel: (E.1) Activity goal completion view showing overall activity goal completion percentage. (E.2) Activity view displaying the detailed activities over time. We see reasonable activity levels which do not explain the fatigue reported by the subject. The most likely explanation of the fatigue and drowsiness being reported is thus apnea.

height, initial reported weight, and current weight. Patient-reported symptoms (sleep, fatigue, pain, and drowsiness) can be input into the interface.

To assess body composition and identify if the patient is at risk for sarcopenia or sarcopenic obesity, we track temporal trends in lean mass index (LMI) and fat mass index (FMI), using the following standard formulas [39]:

$$FMI = \frac{\text{Fat Mass Weight}(kg)}{(\text{Height} * \text{Height})(m^2)} \quad (1)$$

$$LMI = \frac{\text{Weight} * \left(1 - \frac{\text{Fat Ratio}}{100}\right)(kg)}{(\text{Height} * \text{Height})(m^2)} \quad (2)$$

where Fat Mass Weight represents the total weight of fat in the body, and Fat Ratio is the proportion of fat in the body.

To facilitate subject-specific monitoring, our framework instantiation was created using JavaScript, and incorporates the D3.js and React libraries. To ensure the security of user data, we implemented OAuth 2.0 for access, requiring user authentication and permission prior to accessing and visualizing personal data.

III. Results

Our multi-device platform leverages commercially available wearable sensor technologies and smart scales, smartphones, and web APIs to collect and visualize in a secured web-based visual interface real-time data related to activity, sleep, and body composition (Fig. 1).

A. System Components and Architecture

The system comprises four components: (a) a wearable sensor device supporting activity, heart rate, and sleep monitoring (Fitbit Sense 2); (b) a smart scale supporting weight and body mass monitoring (Withings Body+); (c) a smartphone capable of running the Fitbit and Withings mobile apps; and (d) a web-based graphical interface.

We selected the Fitbit and Withings Scale due to their popularity, affordability, and user-friendly design for tracking activities and weight. The Fitbit has been utilized in numerous studies to analyze sleep patterns and heart rate and is a well-established device in activity tracking in biomedical research [1], [12]. Similarly, the Withings smart scale has been

Fig. 3: Example sleep analysis. (A) The subject reports experiencing fatigue and drowsiness. (A) The sleep view shows sleep efficiency scores for a selected month, with color representing sleep scores. Grey indicates the current selected date. The subject has overall good sleep efficiency, with above 89% on average. (B) The sleep stages view shows the distribution of sleep stages over time, indicating the total minutes spent in each stage, which is color-coded according to the sleep stage. The subject spent less time waking, confirming healthy sleep patterns.

validated for studying weight changes [6], [7]. Additionally, these devices are affordable and easy to use at home. Both Fitbit and Withings devices connect to mobile applications via Bluetooth, which allows users to wirelessly upload their daily data and explore them within the apps. Synced data are automatically uploaded to the respective cloud servers anytime a user accesses the app.

The web-based platform, currently hosted at hnc.evl.uic.edu, offers a user-friendly interface to access and explore health monitoring data, including body composition, sleep analysis, and activity patterns over time. In a typical clinical study, patients are provided with a Fitbit smartwatch and a Withings scale, with credentials issued by their care team (Fig. 1). The patients then track daily health data at home, which is uploaded to the cloud via the patient's smartphone. The care team can then access and explore the data remotely through the platform interface. The platform uses the issued login credentials to access the data securely. Once access is granted, the platform then makes web API calls to retrieve the data. To enhance security, data queried is removed upon session termination and not stored.

B. Data Visualization Design

We designed the interface based on constructive and detailed feedback from our collaborators using a parallel prototyping approach [40]. The interfaces comprises four views: 1) the demographics and PRO information panel displays the subject demographics and self-reported outcomes (Fig. 2.A); 2) the body composition panel assists in identifying sarcopenic obesity (Fig. 2, C.1, C.2); 3) the sleep analysis panel aids in exploring sleep data and identifying sleep disturbances (Fig. 2, D.1, D.2); and 4) the activity panel assists in exploring daily activities (Fig. 2, E.1, E.2).

The top navigation panel (Fig. 2.B) provides options for exploring data on a yearly, quarterly, monthly, or weekly basis. Users can also select a custom range to explore the data. Selecting a date range will trigger relevant web API calls to retrieve the corresponding data. By default, the system displays data from 30 days to the current date.

1) Demographics and PRO Information Panel: The information panel (Fig. 2.A) displays demographics such as name, age, height (meters), initial weight (kg), and current weight (kg). Patient-reported outcomes such as sleep, fatigue, pain, and drowsiness can be input on a scale of 0 to 10, with 0 representing the best state and 10 indicating the worst. Logging out will clear all the data stored in the session storage for enhanced security.

2) Body Composition Panel: The body composition panel comprises two charts. The left chart illustrates the Lean Mass Index (LMI) versus the Fat Mass Index (FMI), highlighting the risk of sarcopenia (Fig. 2.C.1). The chart is divided into four quadrants based on LMI and FMI values: Sarcopenic Obese, Low Lean Mass, High Lean Mass, and Obesity. We mark patients at risk of sarcopenia when their LMI is below $16.7kg/m^2$ for males, $13.8kg/m^2$ for females, and the average between the two ($15.25kg/m^2$) when user-reported sex is unspecified, based on reports in the literature [41]. Obesity, including sarcopenic obesity, is determined based on FMI above $9kg/m^2$ for males, $12.6kg/m^2$ for females, and the average between the two ($10.8kg/m^2$) [42]. By default, the chart displays the current condition as a dot marker. The chart can also show the trend over time, where the overall LMI versus FMI trend for the selected period is shown with dots and links. Each dot represents the FMI and LMI values aggregated weekly, color-coded from light green to green, with green indicating the most recent data. Links are utilized

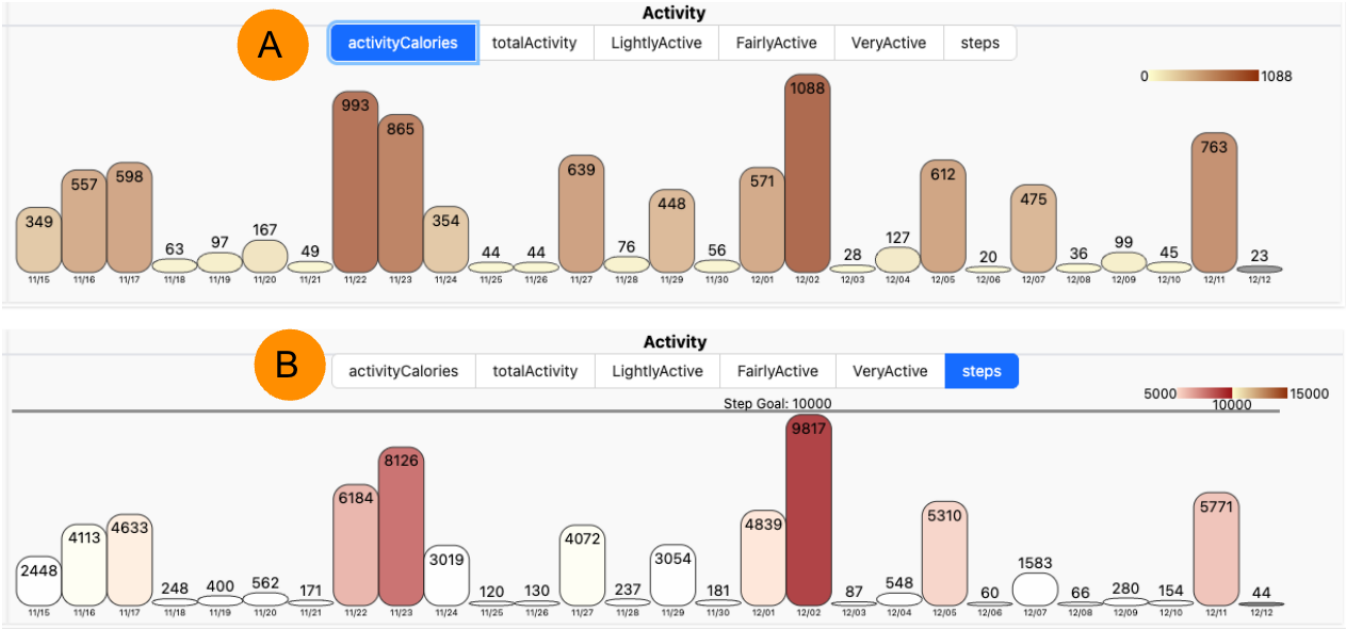

Fig. 4: Daily activity monitoring in the Activity Panel. (A) Activity calories view showing the number of calories burned each day over a month. (B) Steps view showing the daily step count throughout the month, color coded based on the steps. The black line illustrates the step goal established by the subject.

to depict the trend over time. Hovering over each dot reveals information about FMI, LMI, and weight.

The right chart displays body composition over time, enabling the observation of weight, muscle mass ratio, and fat mass ratio trends (Fig. 2.C.2). These trends can be explored weekly or monthly, where the daily weight trend over time is graphed, while selecting quarterly or yearly aggregates the data per month. Each chart dot represents a specific day or month and is color-coded based on the attribute. The current date is highlighted as grey. Selecting a date in this panel will update the data shown in the other panels. Data and attribute values for each dot show as details on demand.

3) Sleep Analysis Panel: The sleep analysis panel allows clinicians to assess a patient's sleep quality and investigate various sleep stages and efficiency during a selected time period based on the data retrieved from Fitbit Sense 2. This panel facilitates exploring oxygen saturation level (SpO2) and heart rates (HR) during a selected day/night, as indicators of sleep disturbance. The panel comprises two charts side by side. On the left, it displays the overall sleep quality score based on the aggregated sleep efficiency score for the selected time period retrieved from the Fitbit (Fig. 2.D.1). The right chart is multi-tabbed and shows SpO2/HR, sleep stages, and sleep efficiency. The chart shows the changes in Spo2 saturation and HR in detail (Fig. 2.D.2). Due to limitations associated with retrieving intraday data from Fitbit via the web API, we explore the sleep data for a selected day. In this view, the per-minute SpO2 and HR data are visualized using line charts, with average SpO2 and HR values represented as dotted lines to indicate variability. The HR is displayed in black, while the SpO2 is color-coded based on the saturation level. Saturation levels in healthy adults range from 94% to 98% [43], and a decline of 3% to 4% from the baseline can indicate potential apnea events [44]. Hence, we considered SpO2 levels below 91% as potential sleep disturbance events, and are shown in red. Darker blue color indicates a saturation level lower than the average daily SpO2, and lighter blue color represents a healthy saturation level. This view also highlights the time the patient spent in different sleep stages, color-coded according to each stage. Additionally, hovering over the stages reveals the exact time and minutes the patient spent in that stage. The sleep stage view details the time, in minutes, that the patient spent in the four sleep stages identified by Fitbit: REM, Light, Deep, and Wake (Fig. 3.B), while the sleep efficiency view shows the efficiency scores (Fig. 3.A). This panel is linked with other panels, and selecting a day will highlight the corresponding data in other panels.

4) Activity Panel: The activity panel view shows the completion of activity goals and detailed activities within the specified time range retrieved from Fitbit. Similar to previous panels, this panel also comprises two charts. The left chart displays the overall goal completion percentage, aggregated based on the selected time range (Fig. 2.E.1). The right chart illustrates the detailed activities over time using multi-tabbed views. For the selected time range, it provides total activity calories (Fig. 4.A), overall activity counts (Fig. 2.E.2), and the number of activities at each level: lightly active, fairly active, and very active, along with the total step count over time (Fig. 4.B), color-coded according to their values. Similarly, this panel is linked with others, and selecting a day will update the other panels.

IV. Discussion and Conclusion

We described the architecture and features of an mHealth software platform to support the near real-time remote monitoring and timely intervention in the treatment and survivorship of cancer patients [45], [46]. For example, head and neck chemo and radiation therapy can result in fatigue and drowsiness [47]–[51], but not necessarily late sleep disturbances, while sarcopenia results in fatigue but not drowsiness or sleep disturbances, and apnea may present with all three symptoms. Integration of multiple consumer-grade devices and measurements in a unified interface can allow radiation oncologists to analyze correlations among multiple factors, to disambiguate among possible causes for patient symptoms, and prescribe in a timely fashion appropriate standard-of-care interventions.

While the standard of care provides potential interdisciplinary interventions to reactively mitigate serious cancer treatment toxicities like sarcopenia, timely detection and insight into the source of such toxicities are essential and could engender earlier intervention or (p)rehabilitation. However, cancer follow-up treatment is currently focused on survival, with follow-up checkpoints aligned with survival milestones. Advanced smart device technologies can enable the remote, distributed monitoring of survivorship toxicities, helping broaden the reach of timely interventions. Daily data from these devices can help the early detection of potentially severe patient conditions, and the implementation of a timely treatment plan.

The design of our platform is informed by a human-centered design process and a decade-long collaboration with radiation oncologists at a large national cancer center, with the explicit goal of supporting a smooth transition into clinical practice. While this work describes the development, architecture, and main features of mEnergy, data collection and an extensive analysis of such data and of its clinical value are beyond the scope of this paper. In future work, we will evaluate this platform in clinical practice.

Our architecture leverages open-access protocols and APIs, allowing expansion and integration of alternative devices and treatment factors in a modular fashion. While consumer-grade devices are subject to market fluctuations, as well as API modifications, these devices nevertheless use the same open standardized protocol (OAuth 2.0) that we leverage in our platform, and API changes require minimal changes in our software. This is a strength of our approach.

In conclusion, our software platform mEnergy supports the near real-time remote assessment of metabolic energy disorders in cancer patients. This platform can aid oncologists in identifying early indicators of muscle-wasting (sarcopenia) due to sleep disturbance, insufficient weight recovery, or reduced/limited activity. This approach paves the way towards a toxicity surveillance environment based on consumer-grade mHealth technologies that can improve the treatment outcomes, quality of life, and survivorship of patients. Our instantiation of this platform for head and neck cancer care integrates consumer-grade smart technology to facilitate near real-time remote monitoring and assessment. The overall approach can transfer to other conditions such as monitoring of sarcopenia in older adults.

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