Sensor Self-Report Alignment (SSRA): Reducing Sun Exposure Assessment Error

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***Abstract*—In population and clinical-based studies, UV wearable sensors are increasingly being used to estimate UV exposure and time spent in physical activity outdoors, which is critical for understanding people's sun exposure behavior. This is particularly important in young adults at risk of developing melanoma as well as melanoma survivors, who want to continue engaging in outdoor activities which are a normal source of recreational physical activity. While wearable sensors provide objective and timely measures in free-living populations, self-report data are needed to provide important contextual information (e.g. sunscreen applied, clothing to protect from the sun) that improve our understanding of health behaviors. However, lack of proper time alignment between sensor and self-report data hinders analyses incorporating these data streams. We formulate this problem of alignment as a network flow graph and propose a Sensor Self-Report Alignment (SSRA) framework to fuse and align data from a chest-worn UV sensor, a hip-worn physical activity sensor, and a self-report. We performed a study on 40 participants (20 melanoma survivors, 20 young adults, who were first-degree relatives of melanoma survivors) who wore a chest-worn UV sensor and a hip-worn physical activity sensor for 7 consecutive summer days (total of 254 days assessed) and provided end-of-day self-reports of sun protection. The proposed SSRA framework provides a new approach to aligning sensor and self-report data, which results in significant changes in measures of time outdoors, as assessed by UV or physical activity sensors. This paper highlights the importance of using wearable sensors and alignment to self-report to reduce sun exposure assessment error, while laying the groundwork for integrating such a framework into population-based studies.**

***Index Terms*—alignment algorithm, wearable sensors, mobile health, self-report, sun exposure, physical activity**

I. Introduction and Background

Subjective self-reports of behavior are prone to measurement error and response bias [1], [2]. To mitigate these problems, objective wearable sensors are being developed to provide more automated measures of participant behavior. Researchers are increasingly deploying both types of measures [3]. However, alignment of sensor and self-report data is often not a straightforward process, due to the need to correct for errors in each measure, thus hindering our ability to correctly account for the unique information each measure can offer [4]. Forgetfulness in end-of-day self-reports can lead to misalignment of data. For example, an individual may misreport an outdoor basketball game as starting at 11:30am as opposed to 10:30am (Fig. 1a), or miss a self-report all together (Fig. 1b).

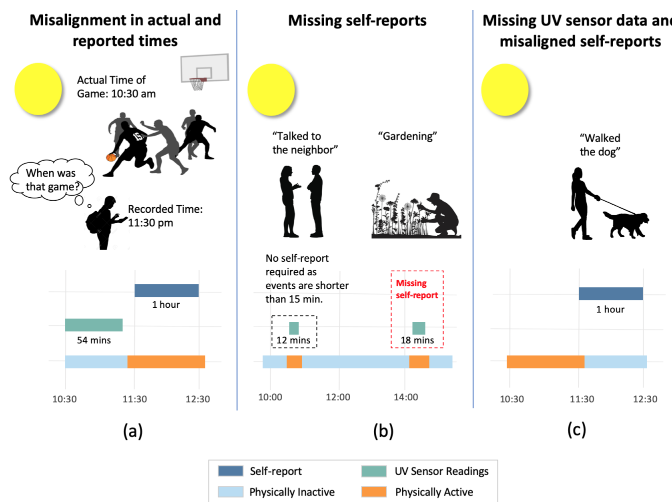


Fig. 1. Challenges in data collected from subjective self-reports: (a) The person misreports the time of the basketball game. The actual and reported times do not align. (b) The person forgets to log taking their dog out for a walk even though sun exposure time was greater than 15 minutes in duration. (c) The person misreports the time they walked their dog. In addition, the UV sensor hasn't captured this exposure event.

Existing wearable physical activity measures, such as actigraphy (ActiGraph GT3X-BTLE, FL), have been used as objective measures to estimate sedentary, light, moderate, and vigorous physical activity. However, given inaccurate self-reports of time spent outdoors, the estimates provided by actigraphy will not correspond to self-reported activity. As depicted in Fig. 1a and Fig. 1c, this misalignment can lead to inaccurate estimates of sun protected outdoor activities. As a result, alignment between self-report, UV sensor readings, and actigraph is needed to improve estimates of UV exposures.

Melanoma survivors are known to be at risk of developing another melanoma [5], and the same patterns of sun exposure that caused the initial melanoma contribute to the risk for a second melanoma [6]. First degree relatives of melanoma survivors also have an increased risk of melanoma [7]. Despite the importance of sun protected UV exposure, even individuals at a risk of melanoma do not generally display high levels of knowledge about UV and are often unaware of the extent of exposure they have received and sustain sunburns. Yet, melanoma survivors also report decreases in their level of physical activity following treatment, potentially in an attempt to decrease their sun exposure [8]. Thus, there is a need for more research designed to understand and intervene upon melanoma survivors' sun exposure and physical activity.

While there has been an attempt at using both self-report and sensor measures of physical activity [9], eating [10], sun exposure [4] and psychological factors (e.g. stress [11]), validation of measures often occurs separately and in different research communities. Behavioral scientists often validate self-report measures using techniques such as Multitrait-Multimethod Matrix (MTMM) [12], and more recently, computer scientists are validating objective measures either through in-lab or in-field visual confirmation [13], [14] or in the event of stress, through in-lab stress induction protocols [11]. However, the focus is often on developing accurate objective measures or combining self-report and sensor information, as opposed to mitigating the errors between the two measures to combine the two and inform a more accurate measure. Our work provides a first step in identifying a framework for alignment of self-report and sensor data by using the strengths and weaknesses of each measurement modality to inform our understanding of the construct.

Recent work has looked into assessing recall of sun exposure by integrating UV dosimeter and self-reported data using a network flow framework [15]. Our effort attempts to validate this approach, while also incorporating a physical activity tracker, to see if alignment not only has a significant effect on estimating time spent outdoors, but also in estimating minutes of physical activity.

Contributions: In this paper, we develop the Sensor Self-Report Alignment (SSRA) framework to align self-report, chest-worn UV sensor and hip-worn physical activity sensor to adjust for misalignment between them. We believe this method is robust to errors resulting from both subjective and objective measures. We evaluate our proposed methods on 40 participants in the real-world with 254 days and 373.32 hours of self-report data, 586.93 hours of UV sensor data and 2467.35 hours of physical activity data. Our proposed methods provide the pervasive community with an ability to understand more accurately the validity of different measures, and a way to more precisely compare subjective and objective measures.

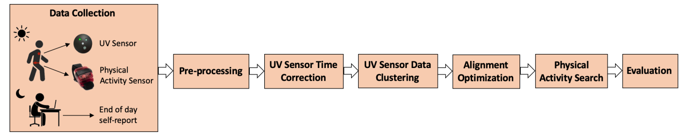


Fig. 2. Framework for aligning self-report measures to sensor data.

II. Study Overview

Forty participants consisting of 20 adult melanoma survivors and 20 young adult first-degree relatives of melanoma survivors, who were not related to the participating melanoma survivors, were recruited to participate in this observational study. Participants without daily access to a computer, smartphone, and wireless internet and those who did not affirm that they would be outdoors for at least 1 hour a day with at least 30 consecutive minutes throughout a 7-day assessment period were excluded from the study. Each participant received an email explaining the research followed by a phone call to schedule an in-person meeting to receive the sensors and install the UV sensor app onto their smartphone. If participants preferred, the sensors and written directions for installing the UV sensor app were mailed to the them. The participants were provided with a UV sensor (Shade ®v1, YouV Labs Inc., NY) to be worn on the left shoulder and a physical activity sensor (ActiGraph GT3X-BTLE, FL) to be worn on the hip and written instructions on using the devices. Informed consent was obtained online prior to completing the baseline survey on the first day of study participation. A link containing the Daily Minutes of Unprotected Sun Exposure (MUSE) and Physical Activity survey was emailed to the participants each day. At the end of each day, participants used this REDCap survey to self-report their outdoor activities and sun protection habits. The survey provided space to record problems with wearing the devices or performing data download from the UV sensor. The study lasted 7 days, and participants received a $100 gift card at the end of the study when the devices were returned.

III. Methods

Our framework for aligning self-report measures to sensor data is depicted in Fig. 2, and is a modified version of prior work [15]. In our current algorithm we provide a method for correcting UV sensor start and end times, and incorporate a physical activity search algorithm to improve alignment during missing UV sensor readings. The data collection phase describes the self-report, UV sensor and physical activity measure. The data pre-processing step prepares the data for analysis, filtering self-report and sensor readings outside the predefined time, and corrects the start and end times of UV sensor readings. The density clustering groups fragments of UV sensor readings into single events and removes readings shorter than 15 minutes. The next step is where self-reports are aligned to UV and physical activity sensors. The final step is of evaluation where we evaluate different metrics reported prior to and post applying the framework.

A. Data Collection for self-report and sensor measures

1) Self-report: The Daily MUSE Inventory [16] is a computerized measure, administered using REDCap [17], and assesses sun exposure based on the outdoor activities that a participant completes during a specific period of time. Each day, participants were asked to report details of all outdoor activities performed for more than 15 minutes between 6am and 6pm. After selecting an activity description (e.g. walking, biking), participants added start and end times, and reported the clothing they were wearing on four separate body regions (head, torso, legs, and feet) by selecting pictures of clothing options with varying coverage, represented by 5 pictures each. Additional items assessed whether they sweat or got wet, and whether they wore sunglasses, or gloves. Participants then reported all instances of sunscreen use, including the time, body sites and SPF of sunscreen applied (or reapplied).

2) UV Sensor: To measure minutes of outdoor exposure and UV dose, the Shade sensor was used [18]. The sensor affixes to clothing with a magnetic ring, which makes it easy to wear and prevents damage to clothing. The Shade UV sensor is shown to provide accurate estimates of UV dose and time spent outdoors [19]. The battery lasts 5 days on a single charge. The sensor is paired to a mobile app (iOS; Android) with transmission of data using Bluetooth Low Energy. This device maintains an internal data log of accumulated UV dose (J/m^{-2}) every 6 minutes; estimates of exposure minutes are rounded up to the closest multiple of 6. Participants wore the UV sensor affixed to their clothing when outdoors; however, it was removed for water-based activities.

3) Physical Activity Sensor: To measure counts of physical activity, the ActiGraph sensor was worn affixed to a belt around the waist with the sensor positioned on the non-dominant hip. Participants wore the sensor when awake; however, it was removed if the participant was engaged in a water-based activity. The ActiGraph data was collected in one-minute intervals (epochs). Each valid minute of wear time was classified according to intensity (counts/min) using commonly accepted cut-points: sedentary ($<$100), light (100-2019) and moderate to vigorous physical activity (MVPA; $\geq$2020) [20].

B. Pre-processing

The analysis was performed on 40 participants and 254 days. From a total of 280 days (7 for each participant), 26 were removed (8 days were removed due to participant noncompliance, minor technical issues, such as dead battery, or lack of sensor wear; 18 days were true zeros with no sun activity recorded). For the time of year and the location where participants were recruited, sun exposure before 6am and after 6pm is known to have minimal adverse effect on the human skin. Hence events recorded before 6am and after 6pm were removed from all three data sources (self-report, UV sensor and physical activity sensor).

After pre-processing, there was a total of 373.32 hours of self-reported data, 586.93 hours of UV sensor data and 2467.35 hours of physical activity sensor data. On average, a participant recorded 9.33 hours of self-report data, 14.67 hours of UV sensor data and 61.68 hours of physical activity sensor data across the 7-day study. An average of 2.13 hours of self-report data, 2.35 hours of UV sensor data, and 9.71 hrs of physical activity sensor data were recorded per day.

C. UV Sensor Start and End Time Correction

Objective sensors often collect data at fixed intervals (e.g, every 1 minute, 6 minutes, 10 minutes etc.) to optimize battery lifetime. The UV sensor used for the study stored UV data at 6 minute intervals (e.g. if a participant had between 1 seconds and 5 minutes 59 seconds of sun exposure, the sensor would record these instances as 6-minute events). An estimation of time outdoors that simply sums all 6-minute readings will overestimate outdoor time. Hence, we devised a method to trim the length of the 6-minute segments that were either first or last in a series of exposure events by extrapolation based on UV dose of the interior 6-minute readings. For events comprised of three 6-minute readings, the 'interior' UV dose was the second event. For events comprised of four 6-minute readings, the 'interior' UV dose was the average of second and third readings. For events longer than 4 6-minute readings, the two most proximal events to the first and last readings were averaged to serve as the 'interior' UV dose. In all UV sensor events more than 3 segments in length, the UV dose for these 'terminal' segments were divided by the average UV dose for the corresponding interior segment(s) and then this value was multiplied by 6 minutes to obtain the minutes of exposure in 'terminal' UV sensor segments. Fig. 3 illustrates this method using a UV sensor event with 7 segments.

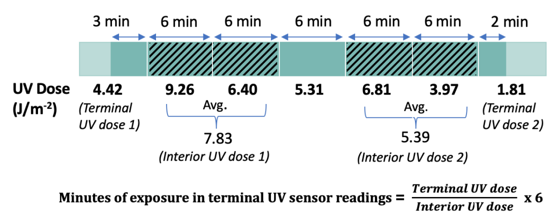
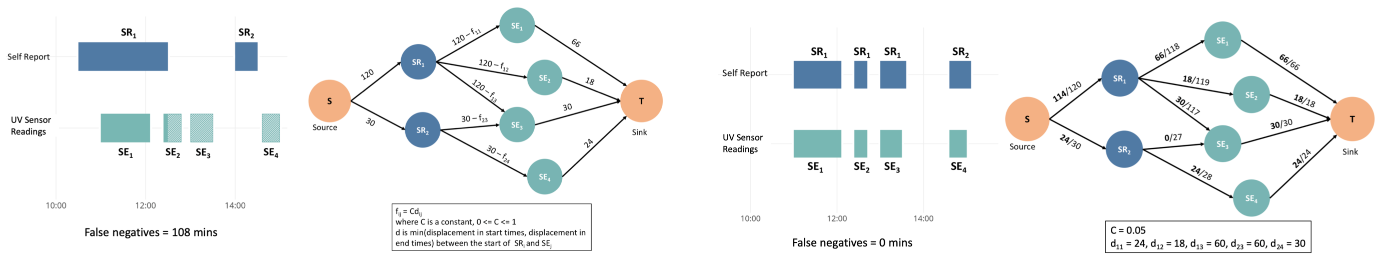


Fig. 3. Illustration of UV Sensor Start and End Time Correction.

D. UV Sensor Data Clustering

Sensor data is often fragmented because the sensor captures participants going into and out of the shade when they are outdoors. However, participants may not report going in-and-out of the shade. Due to the large fragments of UV sensor measurements, clustering of these measurements is necessary to identify isolated events for alignment with self-report. We adopt a similar UV sensor data clustering approach [15] which filters single isolated 6 minute events (since these may range from a few seconds of sun exposure to 6 minutes) and they are shorter than the minimum required duration for a self-report event. We then cluster sensor events that are separated by 6 minutes in duration (this represents a potential in-and-out activity while the individual is outdoor), and so we merge these events together. Once clustering is applied, any remaining



(a) Before alignment

(b) After alignment

Fig. 4. Illustration of the graph flow solution: (a) Illustration of the flow graph construction from self-reports and sensor events. The network optimizes the false negative minutes, by adding the effect of displacement between self-report and sensor events on the flow of the network. (b) Illustration of the residual flow network upon applying Edmonds-Karp algorithm and the aligned self-reports and sensor events.

sensor events that are shorter than the 15-minute minimum duration for self-report are removed prior to alignment.

E. Alignment Optimization

End-of-day self-reports are prone to misalignment in time, due to forgetfulness. We re-align self-reports with the clusters of sensor data by determining an optimal assignment with the objective of reducing false negative minutes, while minimizing the displacement of each self-report.

1) Exhaustive Solution: Given participants may forget the order of their exposure events, given m self-reports and n sensor events, looking at every combination of self-reports with sensor events requires a time complexity of $O(m!+mn)$. Since the order of assignment will impact the total reduction of false negative minutes, an exhaustive approach would be to analyze every combination of self-report alignments.

2) Bounding Exhaustive Solution: Since individuals are unlikely to misalign events that occur farther apart, we attempt to define a bounding box within which self-report can be assigned to a sensor event. To determine the optimal bounding box size, we analyze the distance in time between every unassigned self-report and its nearest sensor event. Based on the difference in start times or end times (the minimum of the two), we then take the mean distance md as the bound for assigning a self-report to a sensor event.

3) Graph Flow Solution: Given a large number of self-reports the exhaustive approach of identifying every possible assignment combination will take a long time to compute and does not account for a self-report being assigned to more than one sensor event. To solve this problem, we reduce the problem to that of a max-flow min-cut problem.

In optimization theory, maximum flow problems involve finding a feasible flow from a single-source to a single-sink such that the flow in the network is maximized [21]. The flow in our problem is considered the number of misaligned minutes that we aim to re-align to sensor measurement events.

Every self-report and sensor event is represented with a node SR_i and SE_j, respectively, in the network. A directed edge is defined between each self-report and sensor event that is within md distance of the self-report start time or end time, where the edge capacity is the maximum number of self-report minutes that can be aligned to a sensor event.

The source node (S) is connected to each self-report node with a directed edge where the capacity is the duration of the respective self-report. Every sensor event node is connected to the sink node (T) with a directed edge where the capacity is the duration of the respective self-report.

We apply the Edmonds-Karp algorithm which is an implementation of the Ford-Fulkerson method and computes it in $O(VE^2)$ time [22], where V is the number of nodes and E is the number of edges in the network. V and E can be further expressed as m+n+2 and m+n+mn respectively where m is the number of self-reports in a day and n is the number of sensor-events in a day.

The problem with this network is it will assign self-reports to sensor event clusters independent of the displacement in time between the self-report and the cluster. As a result, we add a penalty to the flow between self-report and sensor event clusters. We define $f_{ij} = Cd_{ij}$, where d_{ij} represents the minimum of the displacement in start time time or end times between SR_i and SE_j, and C is a weighting that adjusts the effect of d on the network.

Fig. 4a illustrates an instance of misalignment between self-report and sensor reading and the resultant false negative minutes. The participant reports 2 outdoor events (SR_1 and SR_2), however, the UV sensor captures 4 sensor events after clustering (SE_1, SE_2, SE_3, and SE_4). By not aligning the data, it seems the participant missed completely reporting on SE_3 and the majority of SE_2, suggesting 108 false negative minutes. When in reality the participant was probably not as accurate with their start and end times, and SE_1, SE_2, and SE_3 belong to one outdoor activity, with 3 false negative minutes (Fig. 4b). Fig. 4b shows how the self-reports and sensor events are aligned using the SSRA framework.

F. Physical Activity Search

For the self-reports that remain unaligned to UV sensor events after alignment, we examine the description provided for them in the self-reports. Participants choose from a list of 14 responses to answer this question. One of 14 responses (i.e., Seated Activities) implies sedentary physical activity. Other activities imply the participant is performing light to vigorous physical activity. Based on this information, we

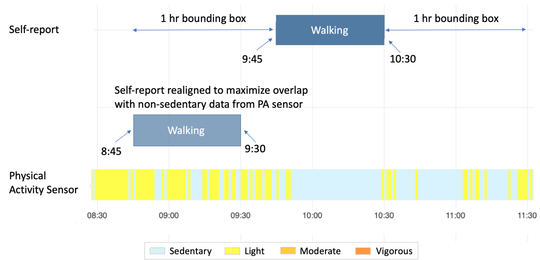


Fig. 5. Illustration of the Physical Activity Search method

search within a bounding box md before the start and after the end of the self-reported outdoor activity. We search at an increment of 1 minute within the bounding box to identify the time frame in which the self-report would overlap with the maximum number of sedentary minutes (for Seated Activities) or non-sedentary minutes (for the remaining 13 non-sedentary activities) reported by the physical activity sensor. Fig. 5 illustrates this technique, with a 1 hour bounding box where a light-intensity walking activity is self-reported to start at 9:45am, when in reality it started at 8:45am, which was found using our search technique.

G. Evaluation

We report the following minute level metrics: 1) false positive self-reported minutes: number of minutes in a day where the participant reported positive sun exposure in the self-report and was recorded as negative sun exposure by the UV sensor; 2) false negative sensor minutes: number of minutes in a day where the participant reported negative sun exposure in the self-report and was recorded as positive sun exposure by the UV sensor; and 3) Jaccard: fraction of the minutes reported in the self-report in agreement with the UV sensor data over the sum of total minutes of positive sun exposure recorded by the UV sensor and false positive exposure reported in the self-report.

Paired two-sided t-tests were performed on the minute-level metrics to assess whether a significant change was observed in them after applying the SSRA framework. Additional paired two-sided t-tests were done on sedentary, light, moderate, and vigorous activity minutes reported by physical activity sensor before and after our framework.

We present the run time (in seconds) and the asymptotic time complexity analysis of the SSRA framework, Exhaustive and Bounded Exhaustive solutions, and report average false negative minutes and Jaccard for each alignment solution.

IV. Results

A. Alignment Algorithm

To determine the optimal size of the bounding box md, we analyzed the offset of the misaligned false positive self-reports from the nearest false negative self-report within a day. The mean offset was 62.37 ± 60.89 minutes. Offsets that were more than 3 standard deviations from the mean were considered as outliers and not included in the analysis. We set the size of the bounding box md (the farthest distance a self-report can be assigned to a sensor cluster) to be 60 minutes.

The value of the weighing term, C for the network penalty was varied between 0 and 1 and best results for average false negative minutes were obtained for C = 0.1.

Table I compares the performances of the alignment solutions. There is a 76% reduction in run time between the Exhaustive (19.18 seconds) and Graph Flow (4.6 seconds) and 52% reduction between the Exhaustive Bounded (9.5 seconds) and Graph Flow solutions. The Graph Flow solution outperforms the Exhaustive solution as it allows for partial assignment of self-reports to sensor events. This contributes towards the reduction of false negative minutes by 3.5% (57.54 mins for Exhaustive, 55.51 mins for Graph Flow), and increase in Jaccard by 7.4% (0.27 for Exhaustive, 0.29 for Graph Flow).

TABLE I
COMPARISON OF THE THREE ALIGNMENT SOLUTIONS

Alignment Solutions	Run time (in secs)	Runtime complexity	Avg. False negative minutes	Avg. Jaccard
Exhaustive	19.18	O(m! + mn)	57.54	0.27
Bounded Exhaustive	9.5	O(m! + mn)	58.53	0.25
Graph Flow	4.6	$O(VE^2)$	55.59	0.29

TABLE II
AVERAGE EVALUATION METRICS OBSERVED FOR PARTICIPANTS (N=40) PRIOR TO AND POST SSRA FRAMEWORK

	Metrics	No Alignment	Post SSRA Framework
Sun Exposure	***Jaccard***	0.18 ± 0.18 *	0.29 ± 0.22 *
	False negative minutes	83.65 ± 32.19 *	55.51 ± 28.31 *
	False positive minutes	33.88 ± 31.05	27.92 ± 32.67
Physical Activity	***Sedentary minutes***	38.21 ± 40.64 *	25.19 ± 17.83 *
	Light minutes	30.56 ± 31.77 *	22.97 ± 27.48 *
	Moderate minutes	9.86 ± 9.77	8.91 ± 8.88
	Vigorous minutes	0.16 ± 0.49	0.14 ± 0.39

* $p < 0.01$

B. Significant Changes to Sun Exposure and Physical Activity

A statistically significant improvement can be observed in the average Jaccard (61% increase) and false negative minutes (33% decrease) prior to and post alignment. There is a 17.3% decrease in false positive minutes, however the difference is not significant (Table II). We also notice a significant decrease in sedentary, and increases in both light and moderate physical activity minutes outdoors.

V. Discussion and Conclusion

Analyses revealed significant changes in sun exposure duration and physical activity estimates after applying the SSRA.

Using this framework enables alignment of more sensor events and self-reports. With minor modifications, the SSRA framework may be extrapolated to other problem domains such as aligning eating self-reports [23] with sensor measures, physical activity self-reports [24] with sensor measures, along with stress sensor and self-report alignment [11].

Understanding accurate personal UV sensor exposure has significant impact in clinical and population settings. These studies ultimately effect treatment as well as urban and environmental policy. Accurate understanding of sun exposure and physical activity is needed in order to provide effective solutions that encourage sun-protected physical activity. Wearable sensors are being increasingly used over approaches that rely predominantly on self-report; however, temporally aligning the two modalities has proven to be a challenge. We provide an efficient SSRA framework that runs in real-time using optimization theory and bounded search from two sensing modalities, a UV chest-worn sensor and a hip-worn physical activity tracker. Our results support the value of SSRA, showing how sun exposure times and physical activity estimates without alignment may misguide treatment recommendations. We show significant reduction in false negative sensor minutes and significant improvement in agreement between sensor and self-reports (Jaccard). We also show significant reduction in sedentary, and increase in light and moderate intensity physical activity levels. Future work will look into testing the SSRA framework on a larger sample size and identifying differences between melanoma survivors and young adults, deploying the SSRA framework across clinical and population-based studies, designing timely interventions to reduce UV exposure and increase awareness of sun protection habits, and testing the SSRA framework in several other health-based applications that combine sensor and self-report measures.

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