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The association of physical activity, heart rate and sleep from an activity tracker with weight loss during a 6-month personalized combined lifestyle intervention: a retrospective analysis

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Abstract

Background Personalizing lifestyle interventions by self-monitoring with wearable sensors can enhance adherence and improve intervention outcomes. It is unknown whether measures from a wearable device can detect lifestyle changes during an intervention. Therefore, the association between individual weight loss with continuous measures from a Fitbit was examined during a personalized SLIMMER combined lifestyle intervention.

Methods A retrospective analysis was performed to assess the association of various Fitbit (Charge 4) measures and self-monitoring behaviors on achieved weight loss during a personalized version of SLIMMER. In this study, 61 people with overweight or obesity were included and were followed one month before the start and six months during a personalized SLIMMER program. Personalization included ambulatory monitoring with an activity tracker and smart scale. Fitbit data was pre-processed to ensure sufficient day- and night- wear-time. Body weight was assessed at the study start and end. Physical activity (PA), heart rate, and sleep were selected from Fitbit output. Their mean change over time before and after the start of the intervention were evaluated with linear mixed effects models and their Spearman correlation with weight loss was investigated.

Findings After pre-processing, 32 subjects with sufficient Fitbit data had 4.9% [1.7–7.7%] weight loss at the end of the program. Step count, moderate PA and vigorous PA increased before the intervention (1667 [0 – 3511] steps/day, $p<0.001$, 38.6 [0.0 – 84.9] minutes/week, $p<0.05$ 65.6 [0.0 – 156] minutes/week, $p<0.05$, respectively), but declined during the intervention (-465 [-1016 – 107] steps/day, $p<0.05$, -28.6 [-40.4 – -16.1] minutes/week, $p<0.001$, -22.0 [-38.2 – -4.2] minutes/week $p<0.05$ respectively). Estimated mean resting heart rate (RHR) correlated moderately with weight loss before ($\rho=-0.46$, $p<0.05$) and during the intervention ($\rho=-0.53$, $p<0.01$). Weight loss

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correlated with the average number of at home weight measurements before ($\rho = 0.37$, $p < 0.05$) and during the intervention ($\rho = 0.41$, $p < 0.05$).

Conclusions This study shows that participants increased physically active behavior before the lifestyle intervention, but this improvement was not maintained during the intervention. RHR is negatively correlated with weight loss before and during the lifestyle intervention and therefore suggesting that participants with a better physiological health status achieved more weight loss.

Keywords SLIMMER, Combined lifestyle intervention, Fitbit Charge 4, Weight loss, Resting heart rate, Physical activity, Wearable sensors, Fitness trackers, Self-monitoring, Obesity, Overweight, Lifestyle behavior

Introduction

Overweight and obesity are well-known risk factors for development of type 2 diabetes (T2D) and other chronic conditions. Overweight accounts for 2.5 billion adults worldwide, of which 890 million are adults with obesity and these numbers grow worldwide [1]. The etiology of obesity is complex and includes socio-cultural, behavioral, treatment side-effects, hormonal, mental and genetic factors [2]. Lifestyle related causes for weight gain include hypercaloric intake, lack of exercise, disturbed sleep, and alcohol abuse [2–5]. These lifestyle factors are interconnected, as sleep quality for example influences dietary and activity habits and vice versa [6, 7]. This shows the importance to gain a better understanding of the interconnectedness of diet, physical activity, and sleep at the individual level when aiming for long-term risk reduction for T2D and other chronic conditions.

Lifestyle improvement can prevent or delay the progression of T2D. Previous studies have revealed that lifestyle interventions combining diet and physical activity (PA) modifications with behavior change reduce the incidence of T2D with 58% among high-risk individuals over a three year period [8]. These effects persist long-term, with lower T2D incidence in the lifestyle intervention group compared to controls after half a decade [9]. A study in the Netherlands on diabetes prevention achieved similar results on T2D incidence reduction after three years (SLIM intervention) [10]. Based on these outcomes a combined lifestyle intervention program was developed to be employed in primary care (SLIMMER intervention [11]), achieving similar effects in terms of weight loss of around 3% after 12 and 18 months [11]. Currently, the SLIMMER combined lifestyle intervention (CLI) is a reimbursed two-year program in the Netherlands where adults who are overweight (BMI 25–30 kg/m^2) and have cardiometabolic risk factors or who are obese (BMI ≥ 30 kg/m^2) are being supported by health care professionals in primary care to improve their lifestyle with respect to dietary intake, physical activity, and behavior change. The program shows modest improvement in body weight (3%), physical activity, and diet, which are sustained at 18 months [11]. However, 10% weight loss is recommended to reduce the risk of T2D optimally [12], so further improvement of such a lifestyle program is essential.

Personalization or tailoring of the lifestyle intervention can improve adherence [13], which can be facilitated with wearable technology for self-monitoring during a lifestyle intervention. An earlier study has shown that personalization leads to significantly improved lifestyle intervention outcomes in the SLIMMER CLI, including weight loss (average of 5% vs 2% of weight loss after 6 months) and drop-out rate (11% vs 26% of drop-outs after 6 months) [14]. Wearable sensors allow for monitoring of physical activity and fitness, heart rate and sleep, but there is limited knowledge which of these health and lifestyle behavior outputs are related to improved weight loss. An earlier study showed that daily step count and minutes of high activity and self-monitoring behavior, in the form of self-weigh-ins and food-logging, are predictors of weight loss during a weight-loss intervention [15]. Currently, it is unclear if other health and lifestyle behavior measures from a wearable device, such as heart rate or sleep, are related to weight loss and subsequently could be used to tailor a lifestyle intervention.

Thus, it is of interest to know if health and lifestyle, as monitored by an activity tracker (Fitbit Charge 4) that assesses physical activity, heart rate and sleep and self-monitoring behavior are associated with individual weight loss during the intervention. Also, it is important to know if outputs from a Fitbit (Charge 4) can detect changes in these health and lifestyle behavior aspects. Therefore, we explored the changes over time in continuous Fitbit lifestyle and health related outputs, to gain insight in how lifestyle behavior and health changes during a lifestyle intervention could be observed with a wearable device. Additionally, we investigated the association between individual weight loss with continuous lifestyle and health outputs from a Fitbit (Charge 4), including physical activity (PA), sleep, heart rate (HR) and self-monitoring behaviors, during the personalized SLIMMER lifestyle intervention. These insights can help to further tailor lifestyle interventions to individual's needs.

Methods

Study design

A retrospective analysis was performed to assess changes over time and the association of various Fitbit health and lifestyle parameters and self-monitoring behaviors on achieved individual weight loss during a personalized SLIMMER combined lifestyle intervention. Data used in this study was part of a larger intervention study that was designed to evaluate the efficacy of personalization on the SLIMMER lifestyle intervention [14]. This research will focus on changes in Fitbit parameters during the personalized SLIMMER lifestyle intervention. The study was approved by a Dutch Medical Ethics Committee in November 2020 (reference: NL75482.028.20) and is in accordance with the Helsinki Declaration of 1975 as revised in Brazil, 2013. The study is registered in a Dutch trial database register https://onderzoekmetmensen.nl/nl/trial/22186 on 11–12-2020. The full intervention with all methods, procedures and samples taken was previously published online [16]. In this section only methods and procedures relevant for the current study will be described.

The study was a parallel, cluster-randomized controlled intervention study consisting of an intervention and a control group. Participants needed to be eligible to take part in the SLIMMER program. This meant people with obesity (BMI > 30) or overweight (BMI > 25) with an increased risk for cardiovascular diseases and/or T2D. An increased cardiovascular risk was defined as having high cholesterol values (total cholesterol ≥ 5 mmol/L, LDL-cholesterol ≥ 3 mmol/L, triglycerides ≥ 2 mmol/L, or HDL-cholesterol ≤ 1 mmol/L) and/or high blood pressure (diastolic > 90 mmHg and/or systolic > 140 mmHg). An increased risk for T2D is defined by an impaired fasting glucose between 6.1–6.9 $mmol/L^{-1}$ or a Diabetes Risk Test score of ≥ 7 points. Further details on the in- and exclusion criteria are documented online [16]. The SLIMMER program was personalized for the intervention group, which included ambulatory monitoring with an activity tracker and smart scale, an extended diagnosis based upon a person's biomedical, contextual, and behavioral data, goals, and personalized lifestyle advice. For the current study we only used data from the intervention group who received the personalized SLIMMER program.

Participants in the intervention arm came to the research facility one month before the start of the SLIMMER program. At this test day participants were provided with a smart body weight scale (the Fitbit Aria Air; Fitbit Inc., San Francisco, CA, USA), and an activity tracker (Fitbit Charge 4; Fitbit Inc., San Fransisco, CA, USA). Participants were monitored during approximately one months period prior (T_{-1} to T_0) and during the first 6 months of the personalized SLIMMER combined lifestyle intervention (T_0 to T_6). Six months after the start, the test day at the research facility was repeated and the monitoring devices were returned. Data collection was from March 2021 to April 2022, during which several COVID-19 pandemic restrictions were in place [17].

Subject inclusion

A total of $n = 61$ people with obesity (BMI > 30) or overweight (BMI > 25) with an increased risk for cardiovascular diseases and/or T2D were included in the personalized SLIMMER intervention of which $n = 54$ participants finished the personalized SLIMMER intervention [14]. All subjects from the intervention arm who had minute to minute Fitbit data and body weight measurements at start and at end of the study were included in the retrospective analysis.

Body weight

The main outcome parameter weight loss was measured at the research facility at start and at the end of the study (InBody, InBody Co., Ltd., Korea). We normalized the weight loss at the end of the study, by dividing the weight at sixth month (T_6) by the weight at the start of the study (T_{-1}). Home-measured weight derived from the smart body weight scale (Fitbit Aria Air; Fitbit Inc., San Francisco, CA, USA) and synchronised with the Fitbit app. Participants were instructed to weigh themselves regularly (at least once a week, but preferably every day), in the morning at the same time and without clothes. Home measured weight was also normalized with the first weight measured with the smart body weight scale, by dividing all home measured weights during the study with the first home registered weight.

Activity tracker data pre-processing

Data from the Fitbit was retrieved from the portal in March 2024 with the Fitbit web Application Programming Interface. The Fitbit Charge 4 measures HR via photoplethysmography and step count (SC) with an accelerometer, which can be retrieved with a sampling frequency of one sample per minute. Next to that, Fitbit provides daily summary variables reflecting the users' PA, HR, and sleep. These daily summary variables are always generated, regardless of wear time of the Fitbit during that day. Therefore, Fitbit data needs to be cleaned or pre-processed to ensure data quality. An overview of the pre-processing steps is shown in Fig. 1. Pre-processing of the data was done in Python 3.12 (extension Spyder 5.5.0).

Currently there is no consensus on how much Fitbit wear-time is needed to reliably interpret physical activity or other health and lifestyle parameters [18]. We

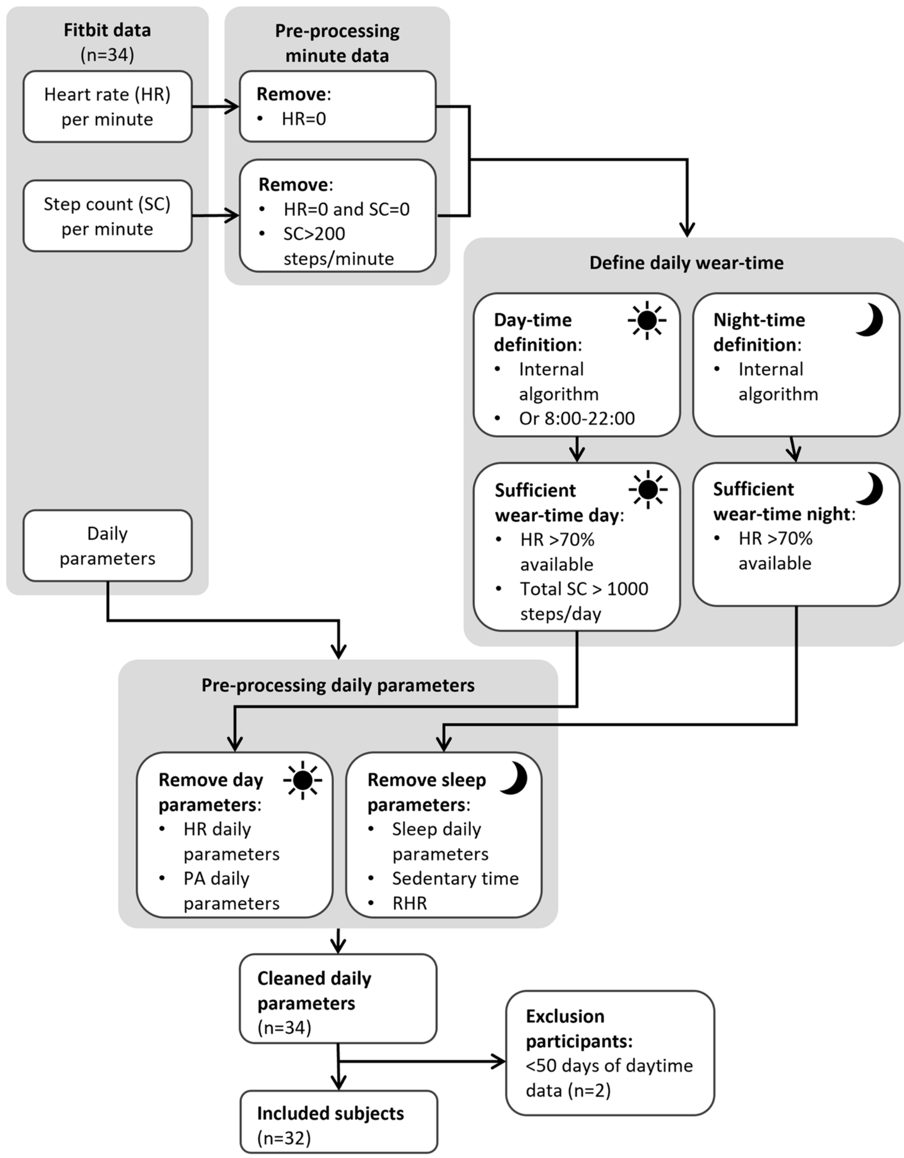

Fig. 1 Overview of the pre-processing of the Fitbit data to ensure quality of Fitbit parameters, by removing Fitbit parameters when the wear time is insufficient. HR, PA and sleep daily parameters are defined in Table 1. HR = heart rate, SC = step count, PA = physical activity, RHR = resting heart rate

determined the wear time of the Fitbit Charge 4 based on a combination of the minute HR and SC data. The activity tracker produces a zero value when no measurement is available for the minute HR and SC data. In SC it is therefore important to make a distinction between zero values from missing data and from true zero values because of inactivity. We defined, similar to previous studies, all zero values in HR as missing data [18–20]. We classified SC as missing data when both HR and step count values were zero [20, 21]. SC higher than 200 steps per minute were seen as outliers and removed [22]. Hereafter, we excluded days and nights with insufficient wear time. First the daytime, and nighttime were categorized by the Fitbit internal sleep algorithm. Daytime was set to be between 8:00–22:00, when sleep was not detected. Most studies report that HR should be available for more than 10 h of the waking hours [18, 19, 23, 24]. Similarly, we selected that HR should be available 70% of the time in both daytime and nighttime as sufficient wear time for respectively day- and nighttime [20]. Days with a daily step count of 1000 or more were included as days with sufficient wear time [18, 20, 23, 25]. PA related parameters were deleted when wear time during the day was insufficient based on the HR and SC criteria. Sleep related parameters were removed, when sleep was not detected by the internal algorithm or night-time wear was insufficient based on HR data. Sedentary time is overestimated when sleep was not measured and resting HR is most accurately measured during sleep [26]. Therefore sedentary time and resting heart rate (RHR) were removed when there was insufficient night-time wear or when the Fitbit did not detect sleep. Subjects with less than 50 days of valid daytime wear were excluded from further analysis.

Model parameters

HR, PA, and sleep domain parameters were retrieved from the Fitbit daily summary parameters. Next to that, we determined self-monitoring behavior as the number of activity registrations per week (the number of activities logged per week by the participants on the Fitbit device), valid Fitbit wear-days per week, and number of weekly weigh-ins on the smart scale. An overview of the used parameters, abbreviations, explanation and domains can be found in Table 1. These parameters were selected from studies using Fitbit in an intervention [15, 27, 28] or because of documented relation with obesity, weight-loss, diabetes [5], energy metabolism [6] or health [29]. Measurement length, and number of days with valid data was calculated for all subjects and parameters over the study period. In addition, the number of days with an weight-measurement from the smart-scale or an exercise recording were determined.

Statistical analysis

We report the median and interquartile range ([IQR]) for the measurement length and data availability. The differences between data availability before and after the start of the intervention was tested with the Wilcoxon rank-sum test. We consider a p-value < 0.05 as significant. After pre-processing data was exported to R (version 4.4.0) for further statistical analysis [30].

Table 1 Parameters used in linear mixed effects models to study change over time and correlation with weight loss during the intervention

Domain	Variable name	Abbr	Unit	Variable explanation	Pre-processing removal	Ref
Heart rate	Resting Heart Rate	RHR	*bpm*	Daily resting heart rate value, which is estimated during sleep	Insufficient day- and night-wear-time	[27]
Physical activity	Step count	SC	*steps/day*	Total steps taken for the day	Insufficient Day-wear-time	[15, 27, 28]
	Sedentary time		*hours/day*	Total minutes sedentary time. Minutes asleep are excluded by Fitbit	Insufficient day- and night-wear-time	[5]
	Light physical activity	LPA	*min/week or min/day*	Total minutes of light physical activity in a week	Insufficient day-wear-time	[15, 28]
	Moderate physical activity	MPA	*min/week or min/day*	Total minutes of moderate physical activity in a week	Insufficient day-wear-time	[15, 28]
	Vigorous physical activity	VPA	*min/week or min/day*	Total minutes of vigorous physical activity in a week	Insufficient day-wear-time	[15, 28]
Sleep	Sleep time		*hours/day*	Total number of minutes the user was asleep across all sleep records in the sleep log	Insufficient night-wear time	[27, 28]
	Sleep efficiency*		*%/day*	Sleep time divided by time in bed (sleep time + sleep restless duration).**	Insufficient night-wear time	[27, 28]
Self-monitoring behaviour	Weigh-ins*		*days/week*	Number of smart-scale recorded weigh measurements per week		[15]
	Tracker worn*		*days/week*	Number of valid day-time measurement per week		[15]
	Activity registrations*		*/week*	Number of activities logged per week by the participants on the Fitbit device		[15]

* Indicates variables which are calculated from Fitbit outputs and are not provided by Fitbit. ** Time in bed and sleep restless duration are both Fitbit outputs. *abbr*. abbreviation, *bpm* beats per minute, *min* minutes

Repeated measures correlation

To assess the correlation between the diverse Fitbit outputs and home-measured body weight derived from the smart body weight scale we used the repeated measures correlation (Rmcorr) [31]. Rmcorr, determines a linear fit for each participant using varying intercepts, for which we used the *Rmcorr*-package [32]. The data was rank transformed per participant before calculating the Rmcorr. This ensures the relation between the variables will be monotonic and linear. We then calculated the Rmcorr (ρ) and corresponding *p*-value. We only report on significant correlations that are considered moderate or higher, which was a |ρ| higher than 0.3. A correlation higher than 0.7 was considered a strong correlation [33].

Mixed effects models

We used mixed effects models to determine the mean and change over time in the activity tracker outputs. Data was split in two parts, one part before the intervention (during run-in period of about 1 month; T_{-1} and T_0) and another part during the 6-month intervention (from T_0 to T_6), as there might be a different effect before and during the intervention. Data before and after the intervention was cut-off to the median length of the measurements, as three participants had an exceptionally long run-in period (T_{-1} to T_0), which had disproportionate effect on the model outcomes.

After data resizing, we fitted an separate linear mixed effects model for every Fitbit parameter before and during the intervention (Table 1), with the *nlme*-package [34, 35]. First, a model was fitted with time as fixed and participant as a random intercept. To normalize the residuals of the models, the pre-processed Fitbit outputs were transformed when needed. Parameters with zero values over more than 25% of the time, were aggregated per week. After removal of days with insufficient wear time, daily averages of VPA and MPA had 32.6% and 28.2% of zeros in the data, respectively. Therefore, VPA and MPA were summed over a week. Hereafter, VPA was transformed with Yeo-Johnson transformation and MPA with square root, to normalize the residuals of the model. Also, LPA and SC were transformed for normality with square root transformation. The random intercept model was compared to a model with a random intercept and slope for each participant. Next, we compared different autoregressive-moving-average (ARMA) correlation structures for time because the model residuals showed significant autocorrelations. The most complex model we attempted to fit was a combination of $p=7$ and $q=7$. Finally, we compared the best random-correlation model with time as fixed effect. We used the model with the lowest Bayesian information criterion (BIC) and only a decrease of 2 was seen as considerable improvement of a more complex model [36]. The models were estimated with restricted maximum likelihood (REML) after selection of the linear mixed effects models to obtain more accurate estimates of the variances of the random effects. Finally, outcomes with a standardized residual greater than 2.5 standard deviations were excluded from analysis [37]. We report on group level average mean and change over time (slope), with 95% confidence intervals and significance level. The difference in mean before and during the intervention was evaluated with Wilcoxon signed-rank test. Figures were made to compare the estimated mean and change over time with the weekly median and IQR of the parameter.

Correlation model estimates and weight

Finally, the correlation between estimated model parameters and weight loss was assessed. For this, each participant's weight loss was Spearman correlated with the model estimates for random intercept and slope over time. We then created a scatter plot showing ranked weight loss versus these model estimates. Using ordinary least squares regression, we estimated the slope and intercept between the ranked variables and calculated the 95% confidence intervals.

Results

Included population and weight loss intervention effects

For the retrospective analysis, 34 (56%) out of the 61 subjects had Fitbit minute data as well as body weight measurements at the start (T_{-1}) and at the end (T_6) of the study period. The minute-to-minute data was extracted from the web Application Programming Interface retrospectively after the study was completed. Data could not be downloaded from the portal for 27 (44%) participants, due to access rights. After pre-processing of the Fitbit data, two subjects (6%) were excluded from analyses as they did not have sufficient day-time Fitbit data (Fig. 1). Table 2 shows the weight loss of the 32 subjects used in this study. Overall, participants lost 4.7% [1.7%-7.7%] of their body weight. In this group, most participants (13, 41%) had moderate weight loss of 5%-10%, 11 (34%) achieved modest weight loss of 0–5% and a small group (19%) gained weight. There are only two subjects (6%) with substantial (>10%) weight loss.

Activity tracker data availability

After Fitbit pre-processing the median length of the measurement was 220 [194.3–249.0] days. Measurement length before the start of the intervention was 35 [19.3–56.8] days and during the intervention 179 [172.8–186.3] days. Three subjects started the study 160 days before the start of the intervention. For these three subjects, whom started measuring 160 days before

Table 2 Demographic data on and weight loss during the intervention for 32 participants included in the retrospective analysis. High education level refers to university or college degrees, middle to upper secondary or vocational training, and low to lower secondary or preparatory vocational education

	Average or number	[IQR] or percentage
Males (n(%))	8	25%
Females (n(%))	24	75%
Age (years)	48.5	[40.8–55.3]
Blood pressure, at start of intervention (mmHg)		
Diastolic	82.8	[76.9–91.5]
Systolic	135.3	[124.6–148.6]
Education level		
High	17	53%
Middle	13	41%
Low	2	6%
Body weight, at start of intervention (kg)	99.5	[88.5–106.8]
BMI, at start of intervention (kg/m^2)	34.8	[30.6–36.7]
Waist circumference (cm)	106.0	[99.8–115.8]
Weight loss during intervention (%)	4.9%	[1.7%-7.7%]
Substantial weight loss (> 10%)	2	6%
Moderate weight loss (5–10%)	13	41%
Modest weight loss (0–5%)	11	34%
Weight gain (> 0%)	6	19%
Weight loss (%)	4.9%	[1.7%-7.7%]

BMI Body mass index

Table 3 Recording length and data availability of the activity tracker during the study period in the included population

	Data availability median [IQR](days)		Data availability ratio [IQR](%)	
Recording length	220	[194.3–249.0]		
After day-time removal	177	[157–224.5]	86.7	[75.6–97.0]
After night-time removal	179	[152.5–213.5]	86.5	[67.5–97.8]
After day- and night-time removal	163.5	[133.5–208.5]	81.7	[58.6–95.6]
Home-measured weight with the smart body weighing scale	54.5	[25.5–123]	27.3	[10.3–54.8]
Exercise recording count	30.0	[14.5–46.3]	13.1	[6.8–21.4]

the intervention, only the 30 days before the intervention were used in further analyses. Table 3 shows the amount of available activity tracker data for the complete study period. Overall, data availability during the study period is high, with data available between 81.7%-86.7% of the days, depending on the pre-processing. On average, participants weighed themselves every 4 days [2–10 days]. People rarely recorded exercise on their activity tracker, with a median of 30.0 days [14.5–46.3] per subject, over the 220-day study period.

Activity tracker data availability before and after start of the intervention (T_0) can be found in supplementary Table S1. There were no significant differences in the amount of activity tracker data availability before and after T_0.

Repeated measures correlation

Figure 2 shows the repeated measures (Spearman) correlation for at home-measured weight with the smart weighing scale and the Fitbit outputs, defined in Table 1. The correlation coefficient is only displayed when the correlation is significant and higher than 0.3. At home-measured weight with the smart scale has a significant moderate correlation with RHR ($\rho = 0.30$, $p < 0.001$). There is a moderate to strong correlation between the PA variables, step count, MPA and VPA. These PA variables all have moderate to strong correlations to the number of activities registered with the Fitbit. Sedentary time and sleep time have a negative correlation of $\rho = -0.63$ ($p < 0.001$). This means that less sedentary time is measured on days with more recorded sleep time. The number of days the tracker was worn correlated strongly with LPA on a weekly basis ($\rho = 0.70$, $p < 0.001$). More significant correlations were found between Fitbit parameters, but all had a weak correlation coefficient ($\rho < |0.3|$).

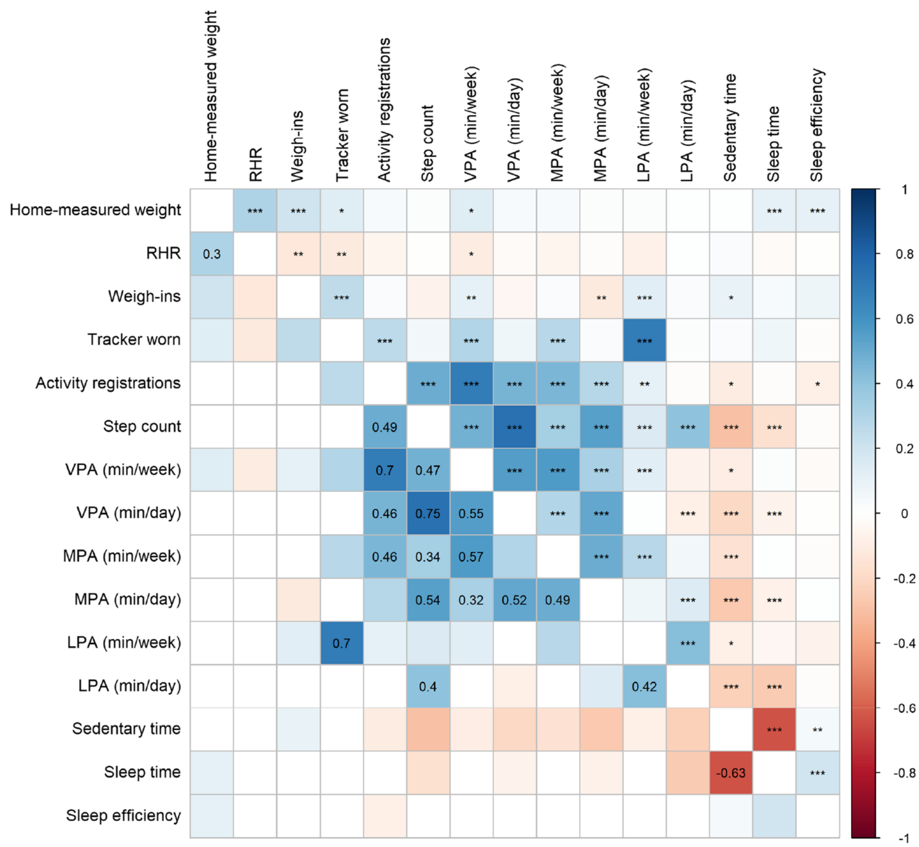

Fig. 2 Repeated measures correlation for self-reported weight and Fitbit parameters, using ranked data. The color indicates correlation strength, with blue a positive and red a negative correlation. The lower triangle shows the correlation coefficient when significant and above |0.3|. The upper triangle shows the significance of the correlation, regardless of correlation value, with * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

Mixed effects models

Mixed effects models were used to assess whether Fitbit parameters changed over time before (from T_{-1} to T_0) and during the intervention (from T_0 to T_6). The structure of the models used can be found in Supplementary Table 2. Since the change in the diverse Fitbit parameters could be dependent on body weight change during the intervention, weight loss groups were added as covariate to the model and evaluated on model fit. Interestingly, adding weight loss groups as covariate did not improve the model fit for any Fitbit parameter (BIC-criterium).

Table 4 gives the estimated mean for all parameters, before and during the intervention. No significant difference was found between the period before and during the intervention. The linear mixed effects estimate for change over time for the Fitbit parameters are presented in Table 5. Figure 3 shows the model estimated means and change over time in blue with the weekly median and IQR over time in grey, for parameters with significant changes over time. In MPA, VPA and in the number of the days the tracker was worn, there is an improvement in lifestyle behavior before the start of the intervention, whereafter these lifestyle behaviors decline during the intervention. Step count and number of activity registrations increased during the 1-month before start of the intervention, but did not show a change during the intervention. LPA and number of weekly weight measurement at home only showed a significant decline during the intervention, but not a change during the run-in period.

Correlation model estimates with weight

To evaluate drivers of individual weight changes, the participant's mean metrics and change over time were Spearman correlated with their change in body weight. All significant Spearman correlations are shown in Fig. 4. Weight loss has the strongest correlation with RHR, with a moderate correlation before (ρ = -0.46, $p < 0.05$) and during the intervention (ρ = -0.53, $p < 0.01$). Next to that, more weekly at home weight measurements is significantly and moderately correlated with weight loss, before (ρ = 0.37, $p < 0.05$) and during the intervention (ρ = 0.41, $p < 0.05$). Participants who increased their number of weight measurements before the intervention achieved more weight loss (ρ = 0.42, $p < 0.05$). Less LPA and smaller

Table 4 Mean estimation from the fitted mixed effects models for each Fitbit parameter

Domain	Variable name	Before intervention (T_{-1}-T_0)		During intervention (T_0-T_2)	
		Est	*[95% CI]*	*Est*	*[95% CI]*
Heart rate	RHR (bpm)	65.8	[62.5 – 69.1]	65.1	[62.2 – 68.1]
Physical activity	Step count (steps/day)	8732	[7566– 9962]	8369	[7345 – 9460]
	Sedentary time (hours/day)	9.0	[7.8 – 10.2]	8.4	[7.0 – 9.8]
	LPA (min/week)	1631	[1465 – 1806]	1645	[1492 – 1805]
	MPA (min/week)	117.8	[86.3 – 154.1]	122.0	[99.0 – 147.4]
	VPA (min/week)	160.1	[112.9 – 218.9]	139.4	[103.2 – 183.3]
Sleep	Sleep time (hours/day)	7.0	[6.3 – 7.6]	7.0	[6.5 – 7.5]
	Sleep efficiency (%/day)	92.0	[88.3 – 95.6]	90.7	[86.4 – 95.0]
Self-monitoring behaviour	Weigh-ins (days/week)	3.2	[2.0 – 4.3]	3.3	[2.4 – 4.1]
	Tracker days (days/week)	6.2	[5.6 – 6.7]	6.5	[6.1 – 6.8]
	Activity registrations (number/week)	5.1	[3.7 – 6.6]	4.8	[3.5 – 6.1]

RHR Resting heart rate, *LPA* Light physical activity, *MPA* Medium physical activity, *VPA* Vigorous physical activity, *min* minutes

Table 5 Total change over time from the fitted mixed effects models for each Fitbit parameter

Domain	Variable name	Before intervention (T_{-1}-T_0) 35 days			During intervention (T_0-T_2) 179 days		
		Est	[95% CI]		Est	[95% CI]	
Heart rate	RHR (bpm)	-1.4	[-3.1 – 0.3]		0.9	[-0.6 – 2.4]	
Physical activity	Step count (steps/day)	1667	[0 – 3511]	***	-465	[-1016 – 107]	
	Sedentary time (hours/day)	-0.3	[-0.9 – 0.2]		-0.2	[-0.7 – 0.3]	
	LPA (min/week)	62.8	[0.0– 126.9]		-78.2	[-152.9 – -1.6]	*
	MPA (min/week)	38.6	[0.0 – 84.9]	*	-28.6	[-40.4 – -16.1]	***
	VPA (min/week)	65.6	[0.0 – 156]	*	-22.0	[-38.2 – -4.2]	*
Sleep	Sleep time (min/day)	1.4	[-19.5 – 22.3]		-15.2	[-47.9 – 17.6]	
	Sleep efficiency (%/day)	-0.1	[-0.1– 0.0]		-0.2	[-0.5– 0.1]	
Self-monitoring behaviour	Weigh-ins (days/week)	0.9	[-0.0 – 1.9]		-2.0	[-2.8 – -1.2]	***
	Tracker days (days/week)	0.8	[0.1 – 1.5]	*	-0.7	[-1.0 – -0.5]	***
	Activity registrations (number/week)	1.6	[0.1 – 3.0]	*	-0.7	[-1.8 – 0.4]	

* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

RHR Resting heart rate, *LPA* Light physical activity, *MPA* Medium physical activity, *VPA* Vigorous physical activity, *min* = minutes

increase in LPA before the intervention had a moderate correlation with weight loss ($\rho = -0.39$ and $\rho = -0.38$ respectively, $p < 0.05$). Finally, people with more sleep time during the intervention achieved more weight loss ($\rho = 0.40$, $p < 0.05$).

Discussion

This paper investigated if a wearable sensor could detect changes in lifestyle behavior and their correlation with weight loss during a lifestyle intervention. Associations between individual weight loss and physical activity, sleep, heart rate and self-monitoring behaviors from a Fitbit (Charge 4), were investigated in a retrospective analysis of a 6 months personalized SLIMMER combined lifestyle intervention. We observed health and lifestyle behaviors as determined by an activity tracker change over time, with significant improvements in physical activity and self-monitoring behavior especially before the intervention at the moment that the activity tracker and weighing scale were being provided to the participants, but this improvement was only partly maintained during the 6 months personalized combined lifestyle intervention. The changes in physical activity were not correlated with achieved weight loss because of the intervention. Additionally, we found that the achieved weight loss was negatively associated with the individuals'

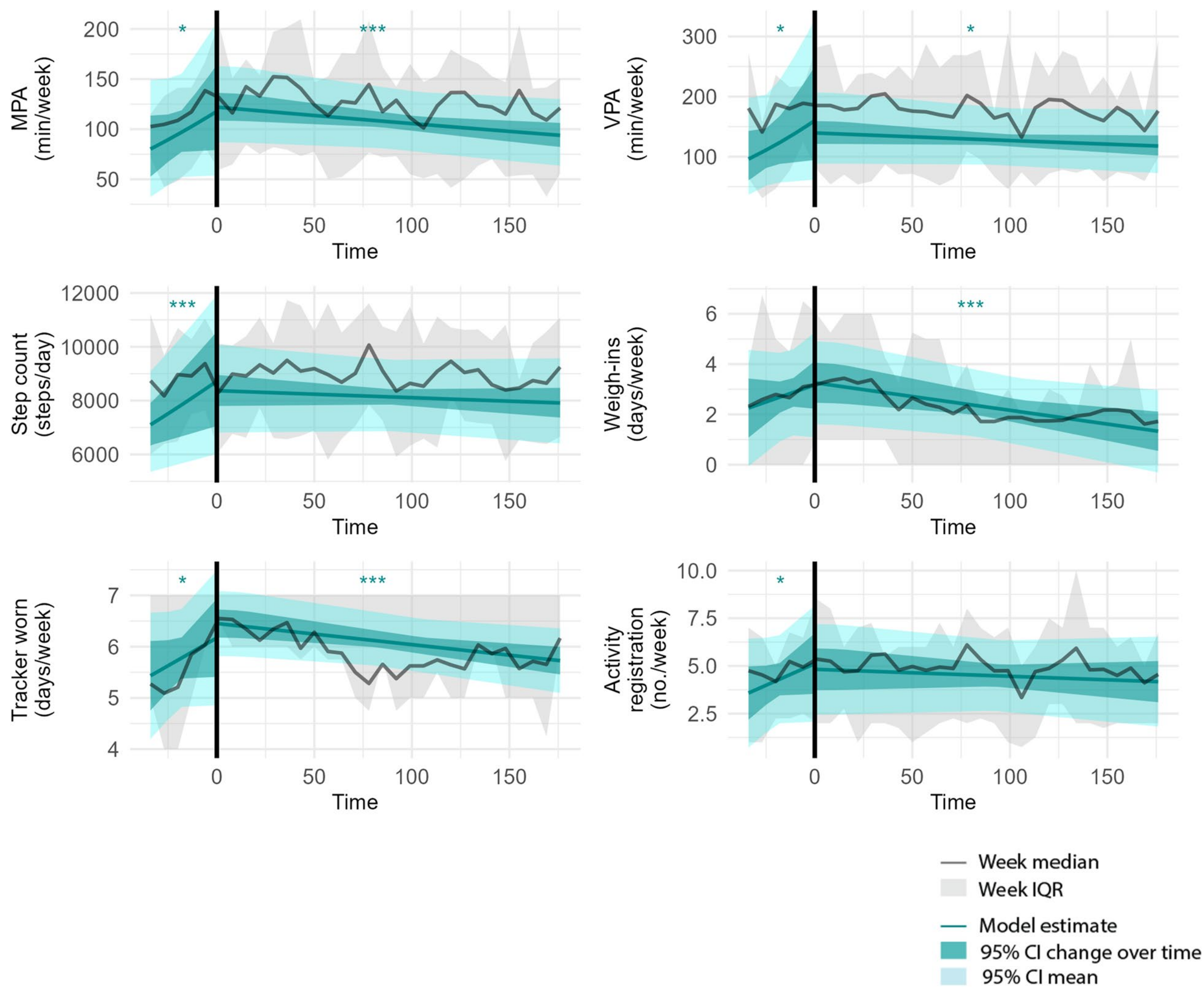

Fig. 3 Linear mixed effect model estimates for mean and changes over time (in blue) and weekly median and IQR (in grey). Significance levels for the models change over time is indicated in blue and differences in estimated means before and after the intervention in black (* = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.)

average resting heart rate (RHR) and positively with the number of home weight measurements, before and during the combined lifestyle intervention. This shows that physiological health status and self-monitoring behaviors have a relation with the achieved weight loss as a result of the combined lifestyle intervention.

Interpretation

The first unexpected outcome is physical activity did not improve during the personalized combined lifestyle intervention, but the improvement in PA takes mainly place during the run-in period, before the start of the combined lifestyle intervention. It seems therefore that the foreseen start of the intervention and the provision of the activity tracker prompts participants to initiate a more physically active behavior, with increased MPA, VPA and SC. Likewise, there is an increase in self-monitoring behavior, as both the number of wear days and the number of exercises recorded with the Fitbit on a weekly basis rise. Unfortunately, these new behaviors slowly relapse to levels at the start of the study, with exception of step count. There is a decrease in LPA, MPA and VPA as well as in self-monitoring behavior. Although, some improvement in PA was seen in the month before the intervention, this was not clinically relevant, as the average before and during the intervention remained the same. An earlier study on the SLIMMER combined lifestyle intervention shows significant improvement in all levels of PA, as measured with questionnaires (SQUASH) and reported higher baseline moderate to vigorous PA

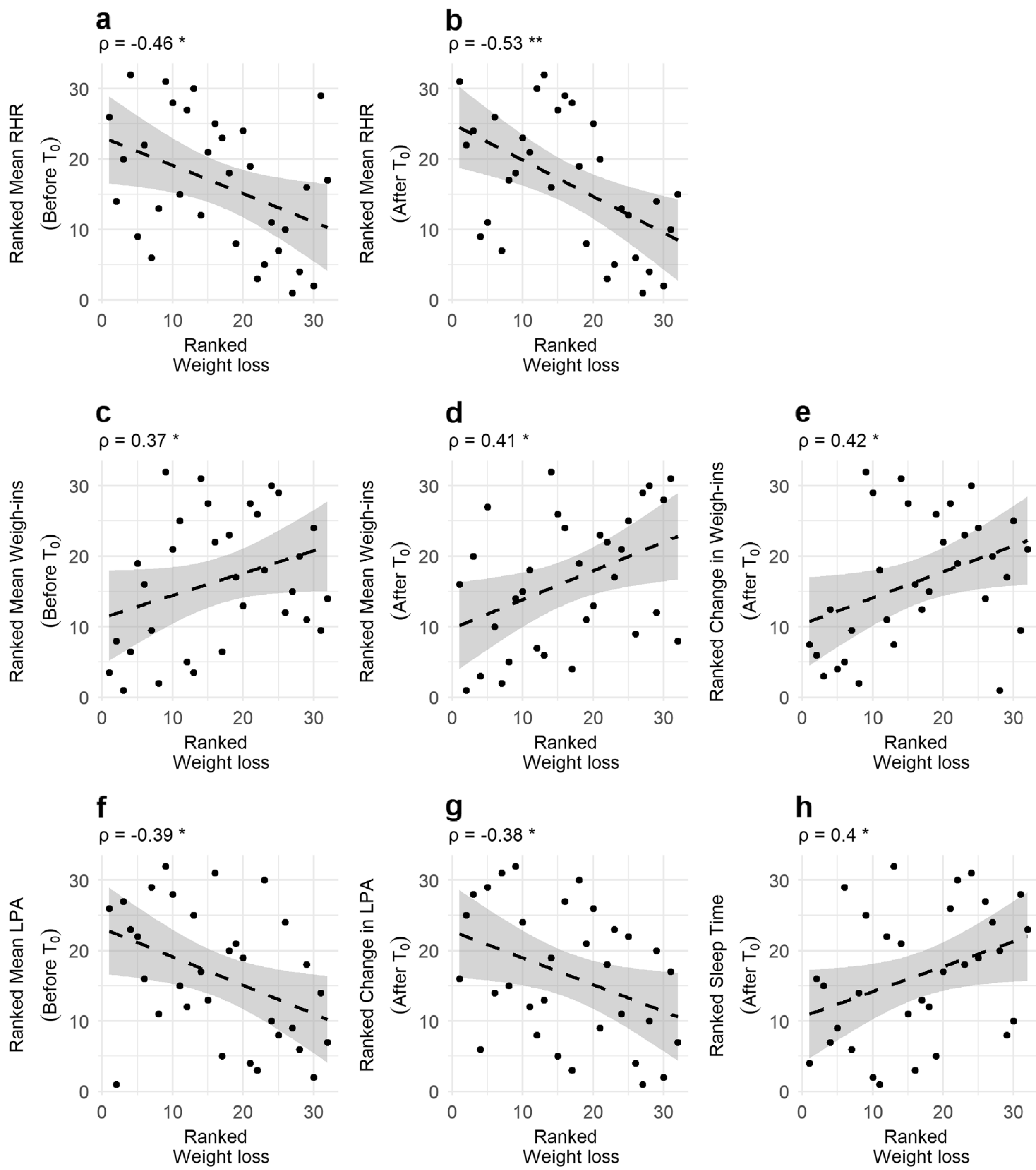

Fig. 4 Scatter plot of weight loss and significantly Spearman correlated Fitbit linear mixed effects model estimates. The line represents the ordinary least squares estimate of the slope and intercept on the ranked transformed variables, with corresponding 95% confidence interval in the grey area

levels and lower light PA levels (354 ± 427 VPA, 593 ± 692 MPA, and 1307 ± 1094 LPA minutes per week vs 160 [112.9 – 218.9] VPA and 118 [86.3 – 154.1] MPA, and 1631 [1465 – 1806] LPA minutes per week) [11]. However, earlier research has shown that self-reporting results in higher moderate to vigorous physical activity (MVPA), when compared to the Fitbit [38, 39]. In the evaluation of the effect of the personalization on lifestyle adherence and health outcomes of this study, self-reported adherence to physical activity guideline did not improve in the intervention arm, in contrast to the control group [40], which is now confirmed by the evaluation of objective measurements on PA through a fitness tracker. A major mediator in physical activity levels might be the COVID-19 restrictions, which were present during the study runtime (2020–2022) [17]. Research by the Dutch government has shown, that Dutch people had altered physical activity patterns during lock-downs [41]. Vigorous exercise decreased, as sport facilities were forced to be closed, but in turn moderate activities, such as walking and cycling, increased. However, the general amount of physical activity did not decrease overall in the Netherlands. Interestingly, in this study more minutes of VPA than MPA were measured by the Fitbit. This discrepancy is likely caused by the differences in MPA and VPA definitions by the SQUASH (used by Dutch government) and Fitbit. Fitbit distinguishes moderate or vigorous physical activity with a combination of HR and SC. Whereas SQUASH determines it by the type of activity or exercise, e.g., running is vigorous activity and cycling is a moderate activity. Past research has shown that PA measured with Fitbit versus self-reports only has weak to moderate correlation. Where Fitbit-measured PA has a stronger correlation with BMI than self-reported PA [39].

The main outcome of this study is that RHR has a moderate negative correlation with weight loss, before and during the intervention and has day-to-day correlation with at home measured body weight. RHR can be seen as a general measurement for overall physical health [42]. RHR differs by age and sex and has shown to be independently associated with increased risk of prediabetes and T2D in overweight people [43], low-grade inflammation in obese [44], metabolic syndrome [45] and overall mortality [42]. RHR decreases with increased physical activity and fitness [46, 47] and physical activity intervention studies have shown to reduce RHR in hypertensive [48] and COPD patients [49]. Against this background, it seems that participants who are generally fitter and already exercise, benefit more from the personalized SLIMMER combined lifestyle intervention in terms of weight loss. In other combined lifestyle interventions targeting physical activity, diet and behavior, RHR decreases significantly in children and (young) adults [50–52]. In this study, we only observed a negative correlation between RHR and weight loss, but a decrease in RHR during the intervention was not found. This may be the result of the unchanged fitness during the study period. In contrast, one previous study showed that a higher RHR, measured during a cardiopulmonary exercise test, predicts weight loss as a result of the lifestyle modification treatment [53]. It was however unclear when RHR was measured in this study. Here we found a RHR of 65.5 bpm (CI [62.2 – 68.7] bpm, average age of 49.6 ± 11.4 years) which is much lower as compared to the aforementioned studies (RHR of 85 ± 9 [51], 84.6 ± 4.2 [44] and 86 bpm [53]), while reporting similar BMI values but in a 10–20 year younger population. Differences in these RHR values might be a result of the RHR measurements timing. In this paper, the RHR is calculated from continuous HR data during the night, whereas in the other papers, RHR is measured at a clinical visit during the day after a few minutes of rest. Research has shown that RHR measurements are significantly lower at night than during the day [54].

In addition to RHR, also at home weight measurements, LPA and sleep time were correlated with weight loss. A higher number of at home weight measurements is correlated with more weight loss during the intervention. Also, a higher increase of at home weight measurements before the intervention might be explained by a higher motivation or engagement with the combined lifestyle intervention. Therefore, self-monitoring of body weight is an important factor for weight loss during an intervention, which has been identified before [15]. Also, frequent self-monitoring of weight has been identified as an important behavior for long-term weight loss maintenance [55]. Surprisingly, participants with lower level of LPA before the intervention and less improvement of LPA during the intervention achieved more weight loss. Whereas, higher level of LPA has been known as a factor contributing to weight loss, and weight maintenance that consequently positively effects health outcomes [56, 57]. An earlier diet and PA weight intervention study with a wearable sensor reported a significant improvement in LPA during the intervention, while starting with similar levels of LPA (1566.7 [1467.7 – 1665.6] vs 1631 [1465 – 1806] minutes per week) [58]. It is therefore unclear how the relation with decreased LPA and increased weight loss in this study originated. Finally, more weight loss was achieved by participants with longer sleep times during the intervention. The measured sleep time here is also lower than expected. In the Netherlands, the self-reported average sleep time is about 8,3 h, which is an hour longer than reported here (7.0 [6.3–7.6] hours) [59]. However, self-reported sleep likely includes time in bed, which is separated by the Fitbit. It is therefore unclear, whether the relation between sleep time and weight loss seen here is reliable. Earlier research has shown inconsistent results regarding sleep time and weight loss during a lifestyle intervention [60].

Strengths and limitations

This retrospective analysis used 220 days of continuous real-world Fitbit data to investigate individual changes in lifestyle behavior and their correlation with weight loss before and during an intervention. This amount of data allowed for in-depth and objective analysis of lifestyle behavior related to RHR, PA, sleep, and self-monitoring. With the data collected before the start of the intervention, we could show that lifestyle behavior changes initiated already before the intervention. The use of linear mixed effect models allowed for individual estimates of lifestyle behavior changes, whereafter these could be explored in relation to individual weight loss. In addition, the data pre-processing ensured that only data with sufficient quality was used in the analysis.

There are limitations to using Fitbit data for assessing health and lifestyle changes. While the Fitbit Charge 4 accurately measures HR at rest [61], step count [62], and sleep–wake-patterns [63], it overestimates steps in free-living conditions [62] and has increased heart rate bias during high-intensity activities [61]. Also, sedentary time may be skewed by short non-wear periods, such as during contact sports, leading to overestimated sedentary time and underestimated physical activity. Additionally, Fitbit's sleep detection algorithm misclassifies lying awake in bed as sedentary time, resulting in a strong negative correlation between sleep time and sedentary time (Fig. 2). Thus, even with data pre-processing, sedentary time might not be an accurate Fitbit outcome. These reported inaccuracies of the device, however, have limited influence on the presented outcomes. The Fitbit device has only two physiological sensors, one for heart rate and one for acceleration. These sensors generate multiple daily summary variables through unknown data processing. This paper shows high correlations among PA variables, such as daily step count, VPA, and MPA, raising questions about whether all these parameters provide additional information.

In this retrospective analysis we used a subgroup of 32 participants from a total of 61 participants in the intervention arm. This subgroup of participants seem to be representative of the whole intervention population, as the currently reported weight loss after 6 months (4.9%) is similar to that of the complete intervention arm (5%) [14]. However, the number of subjects in this study is relatively small.

Future research

This paper and other work using fitness trackers in lifestyle interventions focus on the daily summary values of the Fitbit tracker. In this way, much granularity and details of the Fitbit data is discarded. Minute-to-minute HR and step count data can be used to objectively study daily and weekly behavior patterns. Therefore, as future research the authors would suggest investigating behavior patterns based on minute-to-minute data and associate these to changes weight loss behavior, as these can be used for further personalization of lifestyle interventions.

Conclusion

In this paper we studied the association between individual weight loss with continuous lifestyle parameters from a Fitbit Charge 4 before and during a 6-month combined lifestyle intervention. A lower average RHR before and during the intervention is correlated with more weight loss. This seems to indicate that generally healthier and fitter participants at the start of the combined lifestyle intervention can achieve more weight loss. Daily step count, VPA and MPA improved in the 1-month period before the intervention, but this increase was not maintained during the intervention and MPA and VPA was not significantly higher during the intervention.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s44247-024-00145-1.

Supplementary Material 1. Supplementary Table 1 – Data availability during the study periods, complete study period, before start of lifestyle intervention, and after start of lifestyle intervention.

Supplementary Material 2. Supplementary Table 2 – Fitted mixed effects model structure for each Fitbit parameter before and after start of the lifestyle intervention.

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Authors' contributions

Conceptualization: C.B., U.Y., P.V., and S.W.; Acquisition, data analysis: C.B., U.Y., W.P., T.B., M.C., F.J., and S.W.; Interpretation of data: C.B., U.Y., and S.W.; Writing — original draft and figures: C.B.; Writing — review and editing: U.Y., W.P., H.H., P.V., and S.W.; Supervision: U.Y., H.H., P.V., and S.W. All authors have read and agreed to the published version of the manuscript.

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Data availability

The datasets presented in this publication are available upon reasonable request. Requests to access the datasets should be directed to corresponding author.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki and approved by Medical Ethics Committee 'METC Brabant' (NL75482.028.20) in November 2020 and registered in the Dutch Trial Register https://onderzoekmetmensen.nl/nl/trial/22186 on the 11th of December 2020. Informed consent was obtained from every subjects in this study and included information that the study results will be published.

Competing interests

The authors declare no competing interests.

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