Characterizing usage of wearable device for sleep tracking among women in a real-world cohort from the *All of Us* Research Program

Xintong Li
xli160@u.rochester.edu
University of Rochester

Dillon Dzikowicz
dillon_dzikowicz@urmc.rochester.edu
University of Rochester

Jian Kang
jian.kang@rochester.edu
University of Rochester

Caitlin Dreisbach
caitlin_dreisbach@urmc.rochester.edu
University of Rochester

ABSTRACT

Wearable devices have gained popularity for tracking various health metrics such as physical activity, heart rate, and sleep. Sleep, a vital aspect of overall health, is of particular interest in research and clinical settings. This study aims to characterize the usage of the Fitbit for sleep tracking among a cohort of women from the *All of Us* Research Program. We performed a cross-sectional analysis using the Registered Tier *All of Us* data release (version 7), focusing on female participants who used the Fitbit for sleep tracking. Descriptive measures were employed to understand the cohort, and χ-square tests were conducted to detect differences between groups. Multinomial logistic regression was used to explore relationships between various predictors and different levels of Fitbit usage. A total of n = $7,385$ participants assigned female at birth wore a Fitbit for sleep tracking. Of these, 1,691 (22.90%) were high-frequency users, wearing their Fitbits for more than 13 months. Significant predictors of high (50-75th percentile) and highest (>75th percentile) usage patterns included age, income level, general health status, and self-reported pain levels. Our study underscores the potential of wearable technology to offer personalized health insights and guide health management, particularly for women.

KEYWORDS

Wearable Technology; Fitbit; Data Mining; Sleep; Women's Health

Conflict of Interest: Dr. Dreisbach is an *All of Us* Researcher Ambassador [Pyxis Partners: OD028404] and serves on the *All of Us* Research Program Community Advisory Board. The authors have no other conflicts of interest to disclose.

1 INTRODUCTION

Wearable sensor technology, such as Fitbit devices and Apple watches, has supported the way individuals monitor their health [2]. Wearable devices, in general, have gained significant popularity due to their ability to track a wide range of health metrics, including physical activity, step counts, heart rate, and sleep. Sleep, a crucial component of overall health and well-being, has garnered particular interest within the research and clinical communities [5]. High-quality sleep is associated with numerous health benefits, including improved brain function, improved emotional regulation, and better physical health [15]. Conversely, inadequate sleep has been linked with various adverse health outcomes, such as increased risk of chronic disease progression [16], impaired immune function [6], and reduced quality of life [10].

Understanding sleep patterns for women is crucial because their sleep needs and challenges can differ significantly from those of men due to biological and hormonal differences [7, 8]. Women experience specialized life stages, such as menstruation, pregnancy, and menopause, which can disrupt sleep and affect overall health and well-being [17, 19]. Hormonal fluctuations can lead to issues like insomnia, sleep apnea, and restless leg syndrome, impacting daily functioning, mood, and cognitive performance [14]. Additionally, understanding these patterns can help in tailoring specific interventions and health recommendations to improve sleep quality, thereby enhancing women's physical and mental health and quality of life. Before investigation of sleep patterns and outcomes, research on Fitbit use has identified significant heterogeneity in the use of devices within and between developmental stages with a call for more research on certain subgroups across the lifespan [20].

In this study, our purpose is to characterize the usage of a wearable device (i.e., FitBit) for sleep tracking purposes among a real-world cohort of women from *All of Us* Research Program, a National Institute of Health-funded program to advance healthcare-related research. Understanding how participants use wearable devices to monitor their sleep could support future research on female physiology and intersections of sleep and overall health.

2 METHOD

1 – Data Source. We conducted a cross-sectional analysis using the Registered Tier *All of Us (AoU)* data release (version 7) to understand the individuals who used the Fitbit wearable device. The *AoU* Research Program[1] is a National Institutes of Health-funded effort to gather data from more than one million Americans to accelerate research among marginalized and vulnerable populations. Version 7 contains data from $410,361$ participants and Fitbit data from $15,589$ participants. All participant data were obtained from the *AoU* Research Program, and participants consented to participate in the study and subsequent Institutional Review Board approval was obtained.

2 – Participants. To build our cohort, we used the *AoU* Researcher Workbench cohort builder tool to select an initial group of participants who are identified as female and had Fitbit usage recorded in any of the steps, activity, sleep, and heart rate datasets. See Figure

[1]https://allofus.nih.gov/

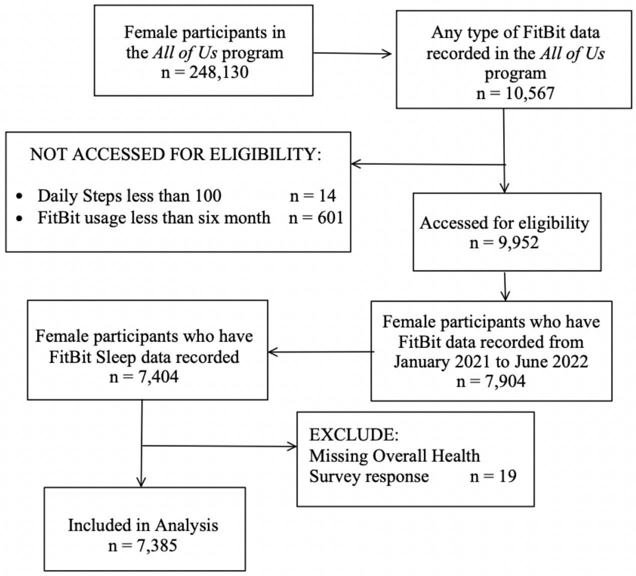

Figure 1: Flowchart of sample selection.

1 for a figure illustrating our final sample size. Among the participants included in the study, we extracted the following covariates: age, race and ethnicity, educational level, annual household income, body mass index (BMI), and number of multiple chronic conditions (MCCs). A diagnosis of MCC was calculate by having 2 or more chronic condition diagnoses present in the participants linked electronic health record data[1]. In addition to the variables mentioned above, we also extracted survey responses from the Overall Health Survey regarding general health, mental health, physical health, average fatigue, pain level estimation, general social quality, and general quality. Data for this analysis represents the timeframe from January 2021 to June 2022 (e.g. the last available date for the Version 7 dataset). The data shows a trend that participant counts became more stable and stopped increasing in the year 2021 (Figure 2). According to the previous work, we excluded individuals who had less than six months of Fitbit data records and had step counts of less than a hundred [13].

3 – Data Preparation. To further analyze the Fitbit sleep records, we created a dataset that categorizes participants into four distinct monthly usage time interval levels based on the number of nights they used the Fitbit for sleep tracking. These tracking levels are divided into four quantiles: less than 25%, 25% to 50%, 50% to 75%, and more than 75%. Users with usage less than 7 months fall into the less than low (<25%) usage category, and those with usage between 7 and 10 months fall into the medium (25-50%) usage category, usage between 10 and 13 months falls into the high (50-75%) usage category, and greater than 13 months falls into the highest (>75%) usage category.

After obtaining the distribution of usage levels, we selected variables as criteria to identify whether there is an associated with responses from self-reported surveys, focusing on basic and overall health. Following methods from previous research, we collected physical measurements of the participants' height and weight [4].

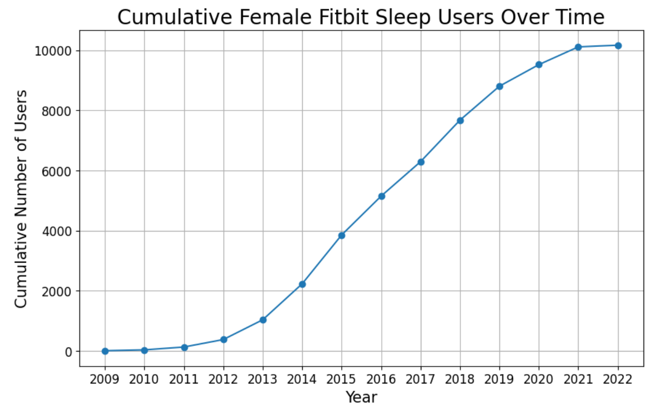

Figure 2: Cumulative Fitbit Sleep of Female Participants Over Time

We calculated BMI using weight divided by height squared for individuals, categorizing them as underweight (under 18.5), healthy weight (18.5 – 24.9), overweight (25.0 – 29.9), and obese (30.0 or higher)[3].

4 – Data Analysis. First, we used descriptive measures to understand the participant cohort and performed χ-square test to detect for difference between groups. We used multinomial logistic regression to understand the relationships between various predictors and the different usage levels of Fitbit data. Before fitting the model, we encoded the categorical variables to prepare the dataset for analysis. We also established reference categories for each variable, as noted in Table 4 to interpret the results accurately. Then we built a multinomial logistic regression model utilizing the 'Statsmodels' library in Python. The model was fitted to the data using the maximum likelihood estimation method. The fitting process yielded parameter estimates, which were then used to calculate the odds ratios for each predictor variable. The odds ratios provide a measure of the association between the predictors and the different levels of Fitbit usage and calculated by $\text{OddsRatio}_{ij} = e\beta_{ij}$ where β_{ij} is the coefficient for predictor j and outcome category i relative to the reference category. We then calculated the 95% confidence interval for the odds ratios. Significance levels (p-value) were set at 0.05.

3 RESULTS

1 – Participant Characteristics. Tables 1 and 2 show differences in key socio-demographic and health variables between engagement groups. Across the entire participant cohort ($n = 7,385$), most individuals were late middle age (65 – 75 years old) ($n = 2,327$, 31.51%), White ($n = 6,212$, 84.12%), non-Hispanic ($n = 6,961$, 94.26%), insured ($n = 7,262$, 98.33%) with an annual income greater than \$100,000 ($n = 2,922$, 39.57%). Over 72.7% of participants ($n = 5,366$) rated their general health as "very good" or "good". Percentages of participants who rated their overall health as "very good" and their mental health as "very good" increased as the engagement groups increased. There were statistically significant differences between tracking groups in age ($p = 0.000$), ethnicity ($p = 0.041$), income ($p < 0.000$), self-reported general health ($p = 0.009$), self-report general physical health ($p = 0.032$), and level of fatigue ($p = 0.004$).

Table 1: Demographics of the Participants with FitBit Sleep Usage (n = 7, 385 Patients in Total).

		Total	Sleep Tracking Usage				p-value
			Low	Medium	High	Highest	
		(n = 7, 385)	(n = 1, 333)	(n = 2, 343)	(n = 2, 018)	(n = 1, 691)	
		Freq. (%)	Freq. (%)	Freq. (%)	Freq. (%)	Freq. (%)	
Age	Early (18 − 39)	1, 876 (25.40%)	413 (30.98%)	575 (24.54%)	482 (23.89%)	406 (24.01%)	**0.000**
	Middle (40 − 49)	1, 290 (17.47%)	238 (17.85%)	409 (17.46%)	351 (17.39%)	292 (17.27%)	
	Late Middle (50 − 64)	1, 538 (20.83%)	256 (19.20%)	476 (20.32%)	461 (22.84%)	345 (20.40%)	
	Late (65 − 74)	2, 327 (31.51%)	371 (27.83%)	758 (32.35%)	635 (31.47%)	563 (33.29%)	
	Advance old (75+)	354 (4.79%)	55 (4.13%)	125 (5.34%)	89 (4.41%)	85 (5.03%)	
Ethnicity	Hispanic	424 (5.74%)	98 (7.35%)	125 (5.34%)	114 (5.65%)	87 (5.14%)	**0.041**
	Non-Hispanic	6, 961 (94.26%)	1, 235 (92.65%)	2, 218 (94.66%)	1, 904 (94.35%)	1, 604 (94.86%)	
Race	White	6,212 (84.12%))	1,086 (81.47%)	1,970 (84.08%)	1,721 (85.28%)	1,435 (84.86%)	0.112
	Black	438 (5.93%)	90 (6.75%)	150 (6.40%)	111 (5.50%)	87 (5.14%)	
	Asian	197 (2.67%)	48 (3.60%)	64 (2.73%)	45 (2.23%)	40 (2.37%)	
	Multiracial	161 (2.18%)	34 (2.55%)	54 (2.30%)	40 (1.98%)	33 (1.95%)	
	Unknown	377 (5.10%)	75 (5.63%)	105 (4.48%)	101 (5.00%)	96 (5.68%)	
Health Insurance Status	Insured	7,262 (98.33%)	1,312 (98.42%)	2,295 (97.95%)	1,990 (98.61%)	1,665 (98.46%)	0.477
	Uninsured	92 (1.25%)	< 20 (1.28%)	33 (1.41%)	23 (1.14%)	< 20 (1.12%)	
	Unknown	31 (0.42%)	< 20 (0.30%)	< 20 (0.64%)	< 20 (0.25%)	< 20 (0.41%)	
Employment Status	Employed	4,450 (60.26%)	790 (59.26%)	1,420 (60.61%)	1,202 (59.56%)	1,038 (61.38%)	0.546
	Unemployed	2,390 (32.36%)	427 (32.03%)	751 (32.05%)	670 (33.20%)	542 (32.05%)	
	Multiple	501 (6.78%)	104 (7.80%)	157 (6.70%)	136 (6.74%)	104 (6.15%)	
	Unknown	44 (0.60%)	< 20 (0.90%)	< 20 (0.64%)	< 20 (0.50%)	< 20 (0.41%)	
Annual Income	Less than 25,000	563 (7.62%)	123 (9.23%)	179 (7.64%)	146 (7.23%)	115 (6.80%)	**0.000**
	25,000 to 50,000	1,139 (15.42%)	262 (19.65%)	358 (15.28%)	287 (14.22%)	232 (13.72%)	
	50,000 to 100,000	2,353 (31.86%)	418 (31.36%)	754 (32.18%)	660 (32.71%)	521 (30.81%)	
	Greater than 100,000	2,922 (39.57%)	457 (34.28%)	923 (39.39%)	819 (40.58%)	723 (42.76%)	
	Unknown	408 (5.52%)	73 (5.48%)	129 (5.51%)	106 (5.25%)	100 (5.91%)	
Highest Level of Education	Up to High School	27 (0.37%)	< 20 (0.38%)	< 20 (0.47%)	< 20 (0.25%)	< 20 (0.35%)	0.233
	High School Graduate/GED	403 (5.46%)	83 (6.23%)	130 (5.55%)	101 (5.00%)	89 (5.26%)	
	Some College	1,709 (23.14%)	319 (23.93%)	556 (23.73%)	426 (21.11%)	408 (24.13%)	
	College/Advance Graduate	5,209 (70.53%)	917 (68.79%)	1,639 (69.95%)	1,476 (73.14%)	1,177 (69.60%)	
	Unknown	37 (0.50%)	< 20 (0.68%)	< 20 (0.30%)	< 20 (0.50%)	< 20 (0.65%)	
Marital Status	Married/Living with Partner	4,671 (63.25%)	815 (61.14%)	1,481 (63.21%)	1,309 (64.87%)	1,066 (63.04%)	0.059
	Divorced/Separated	1,035 (14.01%)	179 (13.43%)	337 (14.38%)	284 (14.07%)	235 (13.90%)	
	Widowed	267 (3.62%)	44 (3.30%)	84 (3.59%)	73 (3.62%)	66 (3.90%)	
	Never Married	1,378 (18.66%)	287 (21.53%)	431 (18.40%)	338 (16.75%)	322 (19.04%)	
	Unknown	34 (0.46%)	< 20 (0.60%)	<20 (0.43%)	< 20 (0.69%)	< 20 (0.12%)	

BMI groupings and the presence of MCCs were not significantly different.

2 – Sleep Tracking. In total, we analyzed the sleep usage data of n = 7, 385 participants who identified as female and wore a Fitbit for sleep tracking. Among them, n = 1, 691 (22.90%) participants were identified as high-frequency users who wore their Fitbits in the top 25 percentile representing usage of more than thirteen months during the study period. In contrast, n = 1, 333 (18.05%) participants were classified as low-usage users in the lowest 25 percentile. Regarding sleep metrics, in Table 3, we discussed the different sleep variables for users with varying usage levels, the average sleeping time recorded was approximately 5.9 hours per night (standard deviation [SD]: 1.8 hours). Participants spent an average of 6.7 hours (SD: 2.0 hours)in bed each night, with an average awake time of 44.9 minutes (SD: 18.9 minutes). There were statistically significant differences between sleep tracking user groups with increasing time asleep and time in bed as the user group level increases from low to highest.

3 – Predictors of Sleep Tracking Usage. Our results identify several significant variables predicting Fitbit usage group compared to the lowest group (< 25-th percentile). Table 4 shows the predictor variables, odds ratios, and associated p-values. First, with the exception of Advanced Old Age, all other age groups (e.g., Middle, Late Middle, and Late) were more likely than the early age group to use be in the medium or high usage categories ($p < 0.05$). The same relationship did not hold for the highest usage category with participants in the Late Middle age (50 − 64), compared to the Early Age participants, were more likely to be in the highest group compared to the lowest (OR= 1.348, 95% CI = 1.104, 1.645, p = 0.003). Importantly, participants reporting and annual income <$25, 000 (OR= 0.710, 95% CI = 0.518, 0.974, p < 0.000), between $25, 000 to $50, 000 (OR= 0.595, 95% CI = 0.476, 0.744, p = 0.033) and $50, 000 to $100, 000 (OR= 0.828, 95% CI = 0.695, 0.988, p = 0.036), compared to those with an income higher than $100, 000 were less likely to be in the highest sleep tracking usage group compared to the low.

Self-reported pain was a significant variable associated with sleep tracking usage group. Participants with mild (rating 1-3) or moderate (4-7), compared with those with no pain, were more likely to be in the medium (mild [OR= 1.253, 95% CI = 1.051, 1.494, p = 0.012], moderate =[OR= 1.272, 95% CI = 1.007, 1.607, p = 0.044]), high (mild [OR= 1.240, 95% CI = 1.036, 1.485, p = 0.019], moderate = [OR= 1.275, 95% CI = 1.003, 1.620, p = 0.047]), and highest (mild [OR= 1.284, 95% CI = 1.063, 1.550, p = 0.009], moderate = [OR= 1.293, 95% CI = 1.005, 1.662, p = 0.045]), sleep tracking groups.

Table 2: Overall Health Survey Statistics of the Participants with FitBit Sleep Usage (n = 7, 385 Patients in Total).

		Total (n = 7, 385)	Sleep Tracking Usage: Low (n = 1, 333)	Medium (n = 2, 343)	High (n = 2, 018)	Highest (n = 1, 691)	p-value
		Freq. (%)	Freq. (%)	Freq. (%)	Freq. (%)	Freq. (%)	
General Health	Excellent	843 (11.42%)	150 (11.25%)	255 (10.88%)	233 (11.55%)	205 (12.12%)	**0.009**
	Very Good	2,896 (39.21%)	476 (35.71%)	915 (39.05%)	812 (40.24%)	693 (40.98%)	
	Good	2,470 (33.45%)	440 (33.01%)	815 (34.78%)	676 (33.50%)	539 (31.87%)	
	Fair	904 (12.24%)	206 (15.45%)	280 (11.95%)	222 (11.00%)	196 (11.59%)	
	Poor	143 (1.94%)	35 (2.63%)	36 (1.54%)	42 (2.08%)	30 (1.77%)	
	Unknown	129 (1.75%)	26 (1.95%)	42 (1.79%)	33 (1.64%)	28 (1.66%)	
General Mental Health	Excellent	1,278 (17.31%)	222 (16.65%)	401 (17.11%)	353 (17.49%)	302 (17.86%)	0.653
	Very Good	2,820 (38.19%)	488 (36.61%)	885 (37.77%)	772 (38.26%)	675 (39.92%)	
	Good	2,137 (28.94%)	392 (29.41%)	674 (28.77%)	598 (29.63%)	473 (27.97%)	
	Fair	873 (11.82%)	172 (12.90%)	287 (12.25%)	226 (11.20%)	188 (11.12%)	
	Poor	159 (2.15%)	35 (2.63%)	55 (2.35%)	41 (2.03%)	28 (1.66%)	
	Unknown	118 (1.60%)	24 (1.80%)	41 (1.75%)	28 (1.39%)	25 (1.48%)	
General Physical Health	Excellent	675 (9.14%)	113 (8.48%)	208 (8.88%)	191 (9.46%)	163 (9.64%)	**0.032**
	Very Good	2,698 (36.53%)	437 (32.78%)	863 (36.83%)	749 (37.12%)	649 (38.38%)	
	Good	2571 (34.81%)	475 (35.63%)	805 (34.36%)	728 (36.08%)	563 (33.29%)	
	Fair	1,101 (14.91%)	234 (17.55%)	358 (15.28%)	270 (13.38%)	239 (14.13%)	
	Poor	206 (2.79%)	48 (3.60%)	64 (2.73%)	47 (2.33%)	47 (2.78%)	
	Unknown	134 (1.81%)	26 (1.95%)	45 (1.92%)	33 (1.64%)	30 (1.77%)	
Fatigue	Very Severe	85 (1.15%)	24 (1.80%)	< 20 (0.60%)	24 (1.19%)	23 (1.36%)	**0.004**
	Severe	435 (5.89%)	86 (6.45%)	150 (6.40%)	115 (5.70%)	84 (4.97%)	
	Moderate	1,988 (26.92%)	400 (30.01%)	599 (25.57%)	543 (26.91%)	446 (26.37%)	
	Mild	3,552 (48.10%)	606 (45.46%)	1,127 (48.10%)	987 (48.91%)	832 (49.20%)	
	None	1,210 (16.38%)	192 (14.40%)	412 (17.58%)	324 (16.06%)	282 (16.68%)	
	Unknown	115 (1.56%)	25 (1.88%)	41 (1.75%)	25 (1.24%)	24 (1.42%)	
Pain	Severe (8 − 10)	207 (2.80%)	45 (3.38%)	65 (2.77%)	55 (2.73%)	42 (2.48%)	0.279
	Moderate (4 − 7)	1,432 (19.39%)	270 (20.26%)	456 (19.46%)	388 (19.23%)	318 (18.81%)	
	Mild (1 − 3)	3,677 (49.79%)	619 (46.44%)	1,159 (49.47%)	1,037 (51.39%)	862 (50.98%)	
	None (0)	1,542 (20.88%)	292 (21.91%)	491 (20.96%)	417 (20.66%)	342 (20.22%)	
	Unknown	527 (7.14%)	107 (8.03%)	172 (7.34%)	121 (6.00%)	127 (7.51%)	
General Life Quality	Excellent	1,664 (22.53%)	282 (21.16%)	508 (21.68%)	479 (23.74%)	395 (23.36%)	0.117
	Very Good	3,228 (43.71%)	545 (40.89%)	1,018 (43.45%)	901 (44.65%)	764 (45.18%)	
	Good	1,778 (24.08%)	359 (26.93%)	578 (24.67%)	455 (22.55%)	386 (22.83%)	
	Fair	507 (6.87%)	104 (7.80%)	172 (7.34%)	127 (6.29%)	104 (6.15%)	
	Poor	82 (1.11%)	< 20 (1.35%)	26 (1.11%)	22 (1.09%)	< 20 (0.95%)	
	Unknown	126 (1.71%)	25 (1.88%)	41 (1.75%)	34 (1.68%)	26 (1.54%)	
General Social Quality	Excellent	2,086 (28.25%)	348 (26.11%)	693 (29.58%)	577 (28.59%)	468 (27.68%)	0.107
	Very Good	3,021 (40.91%)	552 (41.41%)	912 (38.92%)	842 (41.72%)	715 (42.28%)	
	Good	1,528 (20.69%)	267 (20.03%)	491 (20.96%)	418 (20.71%)	352 (20.82%)	
	Fair	524 (7.10%)	115 (8.63%)	177 (7.55%)	126 (6.24%)	106 (6.27%)	
	Poor	106 (1.44%)	24 (1.80%)	28 (1.20%)	28 (1.39%)	26 (1.54%)	
	Unknown	120 (1.62%)	27 (2.03%)	42 (1.79%)	27 (1.34%)	24 (1.42%)	
BMI Measurement	Underweight (Below 18.5)	51 (0.69%)	< 20 (0.45%)	< 20 (0.47%)	< 20 (0.84%)	< 20 (1.01%)	0.413
	Normal weight (18.5 − 24.9)	1482 (20.07%)	261 (19.58%)	465 (19.85%)	401 (19.87%)	355 (20.99%)	
	Overweight (25.0 − 29.9)	1,565 (21.19%)	285 (21.38%)	509 (21.72%)	425 (21.06%)	346 (20.46%)	
	Obesity (30.0 and above)	2,179 (29.51%)	398 (29.86%)	694 (29.62%)	570 (28.25%)	517 (30.57%)	
	Unknown	2,108 (28.54%)	383 (28.73%)	664 (28.34%)	605 (29.98%)	456 (26.97%)	
Multiple Chronic Condition	Less than two conditions	4,354 (58.96%)	781 (58.59%)	1,370 (58.47%)	1,228 (60.85%)	975 (57.66%)	0.214
	At least two conditions	3,031 (41.04%)	552 (41.41%)	973 (41.53%)	790 (39.15%)	716 (42.34%)	

4 DISCUSSION

The findings from our study describe the recent (2021-2022) female Fitbit users in the *All of Us* Research Program and highlights several key factors associated with Fitbit usage for sleep tracking. Our analysis identified age, income level, general health status, and self-reported pain levels as significant predictors of high (between 50% and 75%) and highest (>75-th percentile) sleep tracking usage patterns.

Middle Age (40-49 years old) and Late Age (65-74 years old) participants were more likely to be high-frequency users, suggesting that these age groups may be more health-conscious or more motivated to monitor their sleep for health-related reasons. This could be due to increased awareness of health risks associated with aging or a greater focus on managing chronic conditions prevalent in these age groups [9]. However, having the presence of two or more chronic conditions was not a significant variable. Future

Table 3: Statistical Summary of Fitbit User Sleep Metrics (n = 7,385 Patients in Total).

		Sleep Tracking Usage				
	Total ($n = 7,385$)	Low ($n = 1,333$)	Medium ($n = 2,343$)	High ($n = 2,018$)	Highest ($n = 1,691$)	p-value
	Mean (Std.)	Mean (Std.)	Mean (Std.)	Mean (Std.)	Mean (Std.)	
Time asleep (hour)	5.9 (1.8)	5.4 (2.2)	6.0 (1.8)	6.1 (1.7)	6.2 (1.5)	**<0.001**
Time in bed (hour)	6.7 (2.0)	6.1 (2.5)	6.8 (2.0)	6.9 (1.9)	7.0 (1.7)	**<0.001**
After wake up (minute)	0.7 (2.8)	0.7 (2.4)	0.7 (2.4)	0.8 (4.2)	0.7 (2.4)	0.555
Time Awake (minute)	44.9 (18.9)	45.4 (18.6)	46.0 (17.0)	39.1 (23.7)	47.6 (16.2)	**<0.001**

research could consider further describing the contribution of multiple chronic condition diagnoses to sleep tracking patterns and the potential for sleep tracking as an intervention for symptoms related to sleep and chronic illness.

Recent research by Li et al [12] found that around seven hours of sleep is optimal for middle and older-aged adults. Participants in our analysis has consistently less than ideal sleep, even in the highest sleep tracking categories. Research focusing just on women in midlife found that both short and long sleep durations and frequent snoring were associated with lower odds of healthy aging over time[18]. While we did have access to self-reported snoring data, it may be that individuals in our participant cohort are experiencing other symptoms impacting sleep and overall quality of life. The value of the *All of Us* Research Program dataset is that the study follows participants as they age, grow, develop, get sick, and recover. There will be more opportunities to study healthy aging, the impact of sleep on overall health, and identifying sleep quality over time.

Income level also appeared as an important factor, with participants earning less than $100,000 annually being less likely to be in the highest sleep tracking usage group. This lower odds ratio might reflect the financial barriers to accessing and maintaining wearable technology or a potential lack of prioritization of health tracking due to other financial stresses. As of May 2024, entry-level Fitbits (Fitbit Inspire 3) are less than $100 with models reaching as high as $399 for smartwatches integrated with Google technology. The wide range of device options and associated costs may be a driver for decreased participation among individuals.

Finally, participants experiencing mild or moderate pain were more likely to be the medium, high, and highest sleep tracking categories. This finding suggests that individuals with mild pain might be using Fitbits to monitor and manage their condition actively. Wearable technology could serve as a useful tool for those seeking to understand the impact of their pain on sleep and overall health, potentially guiding them toward better pain management strategies. Despite these insights, many associations between predictors and Fitbit usage levels were not statistically significant, indicating that the predictors may not strongly influence the different levels of Fitbit usage. This lack of strong associations could be attributed to the complex interplay of various factors influencing health behavior and the limitations of self-reported data, which might introduce biases.

While the *All of Us* Research Program offers an opportunity to examine large-scale data analysis of sleep tracking usage, there are known limitations. First, because the dataset is observational, we do not have access to factors that may be relevant to sleep tracking usage patterns. Second, this study did focus only on female participants. Previous research has identified minimal differences in sleep tracking metrics between male and female participants suggesting that study females as a subgroup may not be as relevant [11]. We argue that more nuanced characterization by sex and age is valuable to understand aging and health transitions over time. While our findings demonstrate trends and associations, the overall influence of these predictors on Fitbit sleep tracking usage levels is limited.

5 CONCLUSION

Our study provides valuable insights into the demographic and health-related factors influencing Fitbit usage patterns during sleep among female participants. Age, income level, general health status, and pain levels were identified as significant predictors. Future research should explore additional health factors and employ longitudinal analysis to capture the nature of health behaviors. Ultimately, our study underscores the potential of wearable technology to offer personalized health insights and guide health management, particularly for women.

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Table 4: Multinomial Regression Results on the Relationship between Predictor Variables and Usage Groups (n = 7,385 Patients in Total).

		Medium vs. Low			High vs. Low			Highest vs. Low		
		OR	95% CI	p-value	OR	95% CI	p-value	OR	95% CI	p-value
Age (reference: Early)	Middle (40-49)	1.303	1.059, 1.602	**0.012**	1.264	1.021, 1.565	**0.031**	1.159	0.928, 1.448	0.193
	Late Middle (50-64)	1.509	1.251, 1.819	**0.000**	1.433	1.182, 1.737	**0.000**	1.348	1.104, 1.645	**0.003**
	Late (65-74)	1.336	1.062, 1.679	**0.013**	1.426	1.129, 1.800	**0.003**	1.169	0.915, 1.493	0.212
	Advance old (75+)	1.382	0.956, 1.996	0.085	1.087	0.738, 1.600	0.673	1.111	0.746, 1.654	0.605
Ethnicity (reference: non-Hispanic)	Hispanic	0.924	0.646, 1.322	0.665	0.886	0.612, 1.282	0.520	0.601	0.402, 0.901	**0.013**
Race (reference: White/Caucasian)	Black	0.960	0.726, 1.270	0.775	0.856	0.637, 1.151	0.303	0.783	0.572, 1.071	0.126
	Asian	0.987	0.666, 1.463	0.947	0.723	0.472, 1.109	0.137	0.772	0.497, 1.202	0.252
	Multiracial	1.078	0.691, 1.683	0.741	0.870	0.541, 1.401	0.568	0.883	0.536, 1.456	0.626
	Unavailable	0.825	0.557, 1.223	0.338	0.943	0.632, 1.409	0.775	1.342	0.888, 2.027	0.163
Employment Status (reference: Employed)	Unemployed	1.024	0.856, 1.225	0.797	1.103	0.918, 1.325	0.295	1.039	0.858, 1.258	0.697
	Multiple	0.933	0.711, 1.223	0.614	0.96	0.726, 1.270	0.776	0.868	0.645, 1.168	0.350
	Unavailable	1.039	0.440, 2.453	0.931	0.925	0.370, 2.313	0.868	0.814	0.311, 2.129	0.675
Annual Income (reference: Greater than 100,000)	Less than 25,000	0.894	0.670, 1.193	0.447	0.862	0.640, 1.162	0.330	0.71	0.518, 0.974	**0.000**
	25,000 to 50,000	0.743	0.605, 0.912	**0.004**	0.688	0.556, 0.851	**0.001**	0.595	0.476, 0.744	**0.033**
	50,000 to 100,000	0.980	0.831, 1.156	0.811	0.973	0.823, 1.152	0.754	0.828	0.695, 0.988	**0.036**
	Unavailable	1.03	0.747, 1.420	0.855	1.005	0.722, 1.399	0.977	1.001	0.713, 1.405	0.996
Highest Level of Education (reference: College/Advance Graduate)	Up to High School	1.167	0.406, 3.354	0.774	0.880	0.277, 2.790	0.828	1.022	0.310, 3.371	0.972
	High School Graduate/GED	0.947	0.702, 1.278	0.721	0.818	0.597, 1.122	0.212	0.987	0.714, 1.365	0.936
	Some College	1.079	0.910, 1.278	0.383	0.915	0.766, 1.092	0.326	1.172	0.977, 1.405	0.087
	Unavailable	0.772	0.290, 2.061	0.606	0.971	0.375, 2.519	0.953	1.173	0.439, 3.133	0.750
General Health (reference: Good)	Excellent	0.884	0.586, 1.334	0.557	0.956	0.630, 1.451	0.832	1.081	0.700, 1.669	0.727
	Very Good	1.016	0.793, 1.301	0.900	1.047	0.814, 1.347	0.724	1.115	0.857, 1.452	0.417
	Fair	0.720	0.532, 0.976	**0.034**	0.852	0.620, 1.171	0.322	0.867	0.624, 1.206	0.397
	Poor	0.640	0.308, 1.331	0.232	1.245	0.583, 2.659	0.571	0.949	0.434, 2.075	0.896
	Unavailable	0.906	0.313, 2.621	0.855	1.121	0.382, 3.286	0.836	1.036	0.328, 3.273	0.952
General Mental Health (reference: Good)	Excellent	0.902	0.695, 1.171	0.437	0.875	0.671, 1.141	0.323	1.011	0.766, 1.335	0.937
	Very Good	0.973	0.810, 1.170	0.772	0.906	0.750, 1.093	0.303	1.038	0.853, 1.263	0.709
	Fair	1.171	0.922, 1.487	0.195	1.090	0.850, 1.397	0.495	1.119	0.863, 1.451	0.394
	Poor	1.254	0.759, 2.072	0.377	1.020	0.597, 1.744	0.941	0.811	0.453, 1.453	0.481
	Unavailable	1.076	0.291, 3.974	0.913	0.987	0.255, 3.825	0.985	0.990	0.235, 4.172	0.989
General Physical Health (reference: Good)	Excellent	1.297	0.839, 2.005	0.241	1.071	0.689, 1.666	0.760	1.106	0.698, 1.754	0.667
	Very Good	1.202	0.937, 1.542	0.148	1.043	0.809, 1.343	0.747	1.107	0.850, 1.442	0.449
	Fair	1.087	0.821, 1.438	0.56	0.872	0.649, 1.172	0.363	0.965	0.711, 1.309	0.817
	Poor	1.115	0.617, 2.015	0.718	0.668	0.351, 1.275	0.221	1.113	0.586, 2.116	0.743
	Unavailable	1.032	0.380, 2.804	0.951	1.009	0.367, 2.777	0.986	1.086	0.373, 3.157	0.88
Fatigue (reference: None)	Very Severe	0.553	0.265, 1.156	0.115	1.101	0.550, 2.205	0.785	1.197	0.594, 2.408	0.615
	Severe	1.146	0.800, 1.644	0.457	1.241	0.852, 1.806	0.261	0.903	0.606, 1.346	0.617
	Moderate	0.912	0.731, 1.139	0.416	1.052	0.838, 1.320	0.665	0.902	0.712, 1.143	0.395
	Mild	1.056	0.876, 1.274	0.566	1.140	0.941, 1.382	0.181	1.015	0.832, 1.239	0.882
	Unavailable	1.032	0.307, 4.259	0.842	0.880	0.211, 3.665	0.86	0.946	0.225, 3.983	0.940
Pain (reference: None)	Severe (8 – 10)	1.037	0.670, 1.606	0.869	1.029	0.655, 1.617	0.900	0.895	0.551, 1.453	0.653
	Moderate (4 – 7)	1.272	1.007, 1.607	**0.044**	1.275	1.003, 1.620	0.047	1.293	1.005, 1.662	**0.045**
	Mild (1 – 3)	1.253	1.051, 1.494	**0.012**	1.240	1.036, 1.485	0.019	1.284	1.063, 1.550	**0.009**
	Unavailable	1.041	0.770, 1.407	0.794	0.838	0.607, 1.157	0.283	1.135	0.823, 1.564	0.441
General Life Quality (reference: Good)	Excellent	0.948	0.709, 1.267	0.716	1.247	0.928, 1.674	0.143	1.028	0.755, 1.400	0.860
	Very Good	1.102	0.898, 1.354	0.352	1.238	1.003, 1.528	0.047	1.13	0.907, 1.408	0.276
	Fair	1.196	0.864, 1.654	0.280	1.146	0.812, 1.616	0.438	1.002	0.698, 1.438	0.990
	Poor	1.100	0.489, 2.472	0.818	1.022	0.439, 2.380	0.96	0.904	0.375, 2.180	0.822
	Unavailable	0.921	0.303, 2.803	0.885	1.249	0.411, 3.796	0.695	0.941	0.283, 3.128	0.921
General Social Quality (reference: Good)	Excellent	1.127	0.893, 1.422	0.315	1.011	0.796, 1.284	0.929	0.857	0.668, 1.101	0.227
	Very Good	0.947	0.783, 1.146	0.577	0.935	0.770, 1.137	0.502	0.896	0.732, 1.098	0.289
	Fair	1.003	0.739, 1.362	0.984	0.842	0.609, 1.165	0.3	0.882	0.629, 1.236	0.465
	Poor	0.816	0.414, 1.610	0.558	0.944	0.475, 1.877	0.87	1.199	0.589, 2.443	0.616
	Unavailable	1.110	0.336, 3.671	0.864	0.917	0.260, 3.237	0.893	0.888	0.238, 3.317	0.860
BMI Measurement (reference: Normal weight (18.5 – 24.9))	Underweight (Below 18.5)	0.814	0.333, 1.927	0.650	1.194	0.511, 2.696	0.679	1.283	0.542, 2.925	0.567
	Overweight (25.0 – 29.9)	1.072	0.872, 1.317	0.511	0.982	0.795, 1.214	0.869	0.914	0.733, 1.139	0.423
	Obesity (30.0 and above)	1.136	0.925, 1.393	0.222	1.067	0.865, 1.316	0.544	1.123	0.904, 1.395	0.293
	Unknown	1.157	0.941, 1.421	0.167	1.128	0.914, 1.391	0.260	1.006	0.807, 1.253	0.960
Multiple Chronic Condition (reference: Less than two conditions)	At least two conditions	1.042	0.887, 1.225	0.616	0.932	0.789, 1.100	0.403	0.999	0.841, 1.186	0.989
Alpha significance of 0.05.										

REFERENCES

[1] Peter Boersma. 2020. Prevalence of Multiple Chronic Conditions Among US Adults, 2018. *Prev Chronic Dis* 17 (2020). https://doi.org/10.5888/pcd17.200130

[2] Silvia Canali, Viola Schiaffonati, and Andrea Aliverti. 2022. Challenges and recommendations for wearable devices in digital health: Data quality, interoperability, health equity, fairness. *PLOS Digit Health* 1, 10 (2022), e0000104. https://doi.org/10.1371/journal.pdig.0000104

[3] Centers for Disease Control and Prevention. 2022. All About Adult BMI. https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html Published June 3, 2022. Accessed May 27, 2024..

[4] Cheryl R Clark, Pamela D Chandler, George Zhou, et al. 2021. Geographic Variation in Obesity at the State Level in the All of Us Research Program. *Prev Chronic Dis* 18 (2021), E104. https://doi.org/10.5888/pcd18.210094

[5] Maristella de Zambotti, Nicola Cellini, Andrew Goldstone, Ian M Colrain, and Fiona C Baker. 2019. Wearable Sleep Technology in Clinical and Research Settings. *Med Sci Sports Exerc* 51, 7 (2019), 1538–1557. https://doi.org/10.1249/MSS.0000000000001947

[6] Sergio Garbarino, Pierluigi Lanteri, Nicola L Bragazzi, Nicola Magnavita, and Egeria Scoditti. 2021. Role of sleep deprivation in immune-related disease risk and outcomes. *Commun Biol* 4 (2021), 1304. https://doi.org/10.1038/s42003-021-02825-4

[7] Yoshinori Kawasaki, Takashi Kasai, Yuka Sakurama, Fumiko Kawana, Nami Shiroshita, and Natsuko Koikawa. 2024. Changes in the Objective Measures of Sleep in Association with Menses Among Female Athletes with Poor Subjective Sleep Quality: Female Athletes with Poor Subjective Sleep Quality Have More Sleep Arousals During Menses. *Nat Sci Sleep* 16 (2024), 381–388. https://doi.org/10.2147/NSS.S449305

[8] Vatsal Krishnan and Nancy A Collop. 2006. Gender differences in sleep disorders. *Curr Opin Pulm Med* 12, 6 (2006), 383–389. https://doi.org/10.1097/01.mcp.0000245705.69440.6a

[9] Bridget S. Lange-Maia, Krina Karavolos, E. F. Avery, et al. 2020. Contribution of common chronic conditions to midlife physical function decline: The Study of Women's Health Across the Nation. *Womens Midlife Health* 6 (2020), 6. https://doi.org/10.1186/s40695-020-00053-0

[10] Seung Lee, Jin-Hwan Kim, and Jung-Ho Chung. 2021. The association between sleep quality and quality of life: a population-based study. *Sleep Med* 84 (2021), 121–126. https://doi.org/10.1016/j.sleep.2021.05.022

[11] Timothy Lee, Yeonsoo Cho, Kyung-Sook Cha, et al. 2023. Accuracy of 11 Wearable, Nearable, and Airable Consumer Sleep Trackers: Prospective Multicenter Validation Study. *JMIR Mhealth Uhealth* 11 (2023), e50983. https://doi.org/10.2196/50983

[12] Yi Li, Barbara J. Sahakian, Jie Kang, et al. 2022. The brain structure and genetic mechanisms underlying the nonlinear association between sleep duration, cognition and mental health. *Nat Aging* 2, 5 (2022), 425–437. https://doi.org/10.1038/s43587-022-00210-2

[13] Helen Master, Jennifer Annis, Sarah Huang, et al. 2022. Association of step counts over time with the risk of chronic disease in the All of Us Research Program. *Nat Med* 28, 11 (2022), 2301–2308. https://doi.org/10.1038/s41591-022-02012-w

[14] Sarah Nowakowski, Jennifer Meers, and Elizabeth Heimbach. 2013. Sleep and Women's Health. *Sleep Med Res* 4, 1 (2013), 1–22.

[15] Kannan Ramar, Rishi K Malhotra, Kimberly A Carden, et al. 2021. Sleep is essential to health: an American Academy of Sleep Medicine position statement. *Journal of Clinical Sleep Medicine* 17, 10 (2021), 2115–2119. https://doi.org/10.5664/jcsm.9476

[16] Catarina Reis, Sónia Dias, Ana Maria Rodrigues, et al. 2018. Sleep duration, lifestyles and chronic diseases: a cross-sectional population-based study. *Sleep Sci* 11, 4 (2018), 217–230. https://doi.org/10.5935/1984-0063.20180036

[17] Joan L Shaver and Nancy F Woods. 2015. Sleep and menopause: a narrative review. *Menopause* 22, 8 (2015), 899. https://doi.org/10.1097/GME.0000000000000499

[18] Honglei Shi, Ting Huang, Yunsheng Ma, A. Heather Eliassen, Qi Sun, and Mei Wang. 2021. Sleep Duration and Snoring at Midlife in Relation to Healthy Aging in Women 70 Years of Age or Older. *Nat Sci Sleep* 13 (2021), 411–422. https://doi.org/10.2147/NSS.S302452

[19] Rosalia Silvestri and Iole Aricò. 2019. Sleep disorders in pregnancy. *Sleep Sci* 12, 3 (2019), 232–239. https://doi.org/10.5935/1984-0063.20190098

[20] Ruth G St Fleur, Shannon M St George, Rita Leite, Marika Kobayashi, Yesenia Agosto, and Danielle E Jake-Schoffman. 2021. Use of Fitbit Devices in Physical Activity Intervention Studies Across the Life Course: Narrative Review. *JMIR Mhealth Uhealth* 9, 5 (2021), e23411. https://doi.org/10.2196/23411