Quantifying Subjective Well-being Using Trends in Weekend Activity

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***Abstract*—The rise in popularity of physical activity trackers provides extensive opportunities for measuring personal health at scale. Coupled with renewed interest in the field of positive psychology, we aim to explore how the quantified self can inform us of well-being. In this paper, we examine Fitbit Charge HR data among a college cohort of 125 students who were measured for two academic years (56 weeks). We assess variations in step counts across a typical week through k-means clustering. From this, we observe a group of students whose step counts were highest during the weekend and a group with significantly fewer steps on weekends (t-test, p <.001). We found these trends stable: persisting across the two academic years measured. Students cluster location correlated to aspects indicating sociability and subjective well-being. We discuss the correlations between these traits and propose that weekend activity levels may serve as a measure for informing one's subjective well-being.**

***Keywords*-mental health; wearables; fitness trackers; physical activity; sociability;**

I. Introduction

In a study from 2005, 9,000 college students across 47 nations were asked to rank values including love, wealth and health. Among the 20 given values, happiness received the highest rating with more than 50% of respondents assigning it the highest rank possible and only 3% indicating they did not value happiness at all [1]. As such an important value, it has become a primary topic of interest in the recent renewal of positive psychology which has led to a breadth of research on positive affect [2].

However, happiness is an ambiguous term as it reflects a variety of aspects of life and is often used interchangeably with subjective well-being (SWB), better defined as "people's emotional and cognitive evaluations of their lives, includes what lay people call happiness, peace, fulfillment, and life satisfaction" [3]. The study of SWB includes measurements, causal factors and underlying theory, all of which are highly debated as they continue to be explored [4].

The growing interest in self-monitoring through wearable technology and personal tracking devices lends itself to such exploration, given computing devices such as Fitbits have been shown to provide reliable tracking of physical activity and reasonable measures of sleep duration [5]–[7]. The benefits of leveraging these data streams are already becoming apparent with observational and experimental studies finding links to SWB [8], [9].

In this paper, we report on a study in which Fitbit Charge HRs were used to monitor a cohort of 125 college students over two academic years. We show that step counts across an average week reveal two types of students: those with high step counts on weekends and those with low step counts on weekends. We find this measure of weekend activity correlates to behavioral traits and aspects of personal health reflective of SWB. We conclude with a discussion of these correlates and propose weekend activity as a measure for informing one's SWB.

II. Methods

A. Study design

The data comes from the NetHealth study conducted at the University of Notre Dame [10]. All procedures were fully approved by the institutional IRB before distribution. The study includes an ongoing collection of demographic, psychometric, social network and physical activity data on 698 students who entered the university as first-year students in the Fall of 2015. An outline of the recruitment process and student sample numbers is provided in Fig. 1. Levels 4 and 5 reference students selected for the analysis in this paper which we address in the next section.

This initial cohort of 698 students was split across three tiers of students based on when they entered the study. Three hundred and ninety-one Tier 1 students were recruited via an interest survey in June 2015 and solicitations made through e-mail and a Facebook page. Selection was based on a first come first serve basis after demographic distributions were met in keeping with the overall demographic distributions of the university. Ninety-seven Tier 2 students were then recruited in November and December 2015, nominated by existing participants in the study. Finally, 210 Tier 3 students entered the study in April 2016. Students received a Fitbit Charge HR either before arriving on campus, after arrival, or in the Spring 2016 semester, dependent on when they entered the study.

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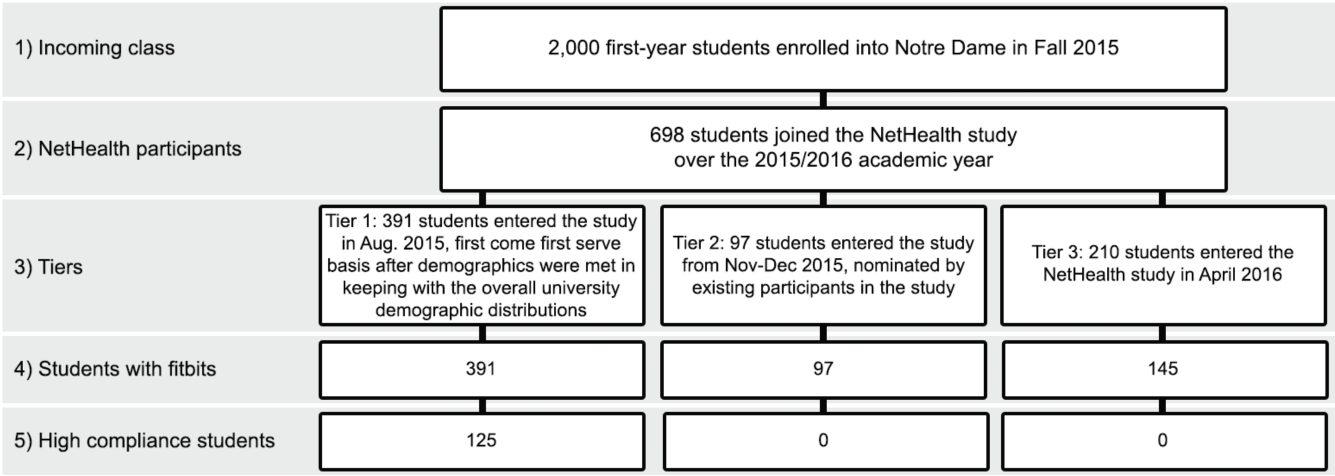

Figure 1: Consort diagram of NetHealth recruitment and students selected for this analysis in this paper.

B. Data collection

Surveys were administered to NetHealth participants once every semester and included questions covering their educational background, personality, student activities, physical assessments, mental health assessments, sleep behaviors, and personal and family demographics. Social network data was collected via a smartphone app which maintains a record of who students contact through calls and SMS. Physical activity data was measured by Fitbit Charge HRs and includes heart rate, active minutes, steps, calories burned, and minutes asleep.

C. Data pre-processing

Data spanned the 2015/2016 and 2016/2017 academic years, comprising approximately 56 weeks. Seasonal breaks were removed from consideration as compliance issues were most severe during these times and days were not representative of a students time on campus [10].

Among the 698 NetHealth participants, 65 students were removed from consideration as they were not issued Fitbits, with reasons ranging from students declining them to dropping the study before the device could be issued (Fig. 1, level 4). To prevent biases stemming from missing data, students with Fitbits were only considered if they met the appropriate compliance threshold. Our compliance threshold required a student to wear their Fitbit 80% of the day or 19 out of 24 hours for that day to be considered *compliant* as this threshold provides a good indication of activity and sleep [10]. A distribution of the number of compliant days in each students *least compliant semester* is shown in Fig. 2. We focus on students least compliant semester to ensure students selected have a sufficient amount of data in each of the four semesters.

As seen in Fig. 2, approximately 400 students had a semester where this compliance threshold was not met or

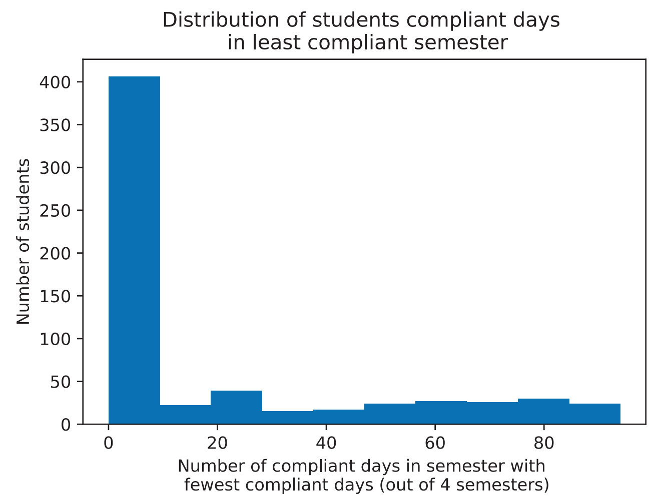

Figure 2: Distribution of students number of compliant days in their least compliant semester across the four semesters measured.

met for only a few days. Two hundred and thirty-three of these students were from tiers 2 and 3. Since they did not enter the study until late Fall 2015 and Spring 2016, they had few to no compliant days for the Fall 2015 semester. Ignoring students with zero compliant days in one of their semesters, the median number of compliant days in a students least compliant semester was 49, approximately *half* of the total days in a semester. Taking the top 50% of compliant students left 125 students in our analysis for this paper (Fig. 1, level 5), with all students meeting our compliance threshold for at least *half* the days in each semester. All 125 students were Tier 1 and therefore active in the study for all four semesters measured. A demographic overview is provided for these students in Table I, with all students ranging between ages 17 and 19. Comparisons were made between the 125 students included in the study and the 508 excluded which we address in Section V.

Daily step counts were averaged by weekday across the 56 weeks. Each student's average week was then normalized using z-normalization to reduce the magnitude of each students step counts, allowing them to be clustered by days they were most/least active instead of by their overall step counts.

III. Results

A. Clusters

Students trends were clustered using k-means clustering, chosen because the centroids the algorithm provides were of primary interest as these represented common trends in step counts across an average week [11], [12]. To ensure an optimal k was used, an elbow plot of the mean-squared error (MSE) across each possible k was drafted. Among all possible options for k, k = 2 provided the optimal MSE for the fewest number of clusters. The algorithm was run across 1,000,000 iterations to ensure optimal centroid seeds were used.

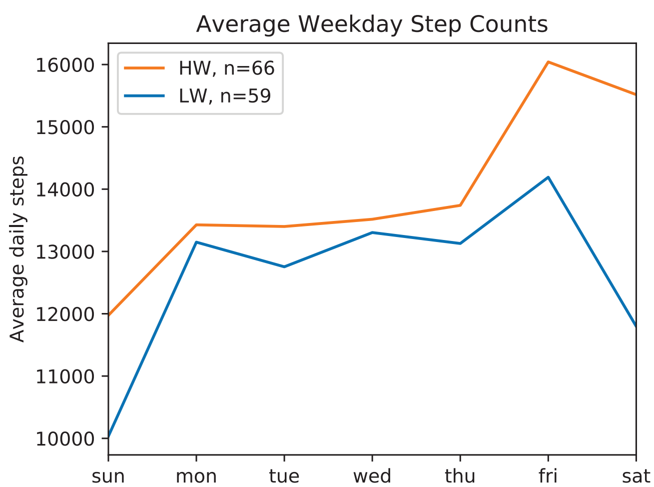

Figure 3: Cluster analysis shows average daily step count patterns for two groups of students: one group with high step counts on weekends (HW), and the other with lower step counts on weekends (LW) [13].

Clustering resulted in two groups of students separated by their step counts over Fridays, Saturdays and Sundays ($t-$tests, $p < .001$), shown in Fig. 3, with no differences occurring Monday through Thursday. The 66 students in the HW cluster (high-weekend) had, on average, 2,000 (12%) more steps on Fridays, 4,000 (26%) more on Saturdays and 2,000 (12%) more on Sundays than the LW cluster (low-weekend) of 59 students with low step counts on weekends.

Trends in step counts over weekends were then examined at the hourly level to determine the specific times at which the HW and LW clusters differed. Fig. 4 visualizes average step counts of each cluster across a weekend. The greatest differences between clusters occurred from 9pm Friday to 1am Saturday, Saturday from 11am to 4pm and 10pm Saturday to 1am on Sunday, with the HW cluster averaging approximately 200 more steps per hour within these time spans ($t-$tests, $p < .05$).

Since weekday step counts were averaged over two academic years for clustering, each semester was analyzed separately to determine the stability of these trends. The HW cluster retained consistently higher step counts on Fridays, Saturdays and Sundays compared to the LW cluster. Differences in steps counts for each day of the weekend were significant across all four semesters ($t-$tests, $p < .01$). No differences were found in any of the four semesters for Mondays, Tuesdays, Wednesdays, or Thursdays. Fig. 5 shows these trends at a daily frequency across the two academic years with HW students having consistently higher step counts on weekends.

B. Descriptive Statistics

Differences in students survey responses were then compared between clusters to better understand the profile of the average student belonging to each cluster. All students completed five surveys covering demographic, psychometric and activity questions. The entrance survey was taken in the summer of 2015 before students arrived on campus and follow-up surveys were taken after each semester. First comparing demographics, we found gender and age insignificant. While we observed a significant Fisher's Exact test for race ($p = .02$), pairwise post-hoc Fisher's tests were insignificant. We report gender and race demographics by cluster in Table II.

Beyond demographics, cluster comparisons were next made using only the summer 2015 survey to isolate any traits students may have which could predispose them to a particular cluster *before* arriving on campus. For each survey response, a $t-$test was completed to note significant differences in responses between clusters. Using an α of .05, we report significant differences between clusters in Table III. We present the change in mean moving from the LW to HW cluster for each attribute by gender to note differences between men and women. For example, HW males gave responses, on average, 18.8% higher than LW males for how much time they spent playing club sports, suggesting HW males spent more time playing club sports than LW males. We also note that *point scale* refers to the range of possible scores i.e. 5 meaning possible scores ranged between 1 and 5.

Activity questions were asked in the form of "How often did you ... during the past year?" with responses based on a numeric scale where lower numbers represented less time spent on the activity. Students in the HW cluster were more likely to participate in varsity ($p = .004$) and/or club sports

Table I: Comparison of demographics between students included in this analysis versus students excluded based on compliance.

demographic		included, n = 125	excluded, n = 508
gender	male	67 (53%)	263 (51%)
	female	58 (47%)	245 (48%)
race	white	83 (66%)	333 (65%)
	latino	21 (17%)	57 (11%)
	asian	12 (9%)	46 (9%)
	black	4 (3%)	34 (6%)
	foreign	4 (3%)	38 (7%)

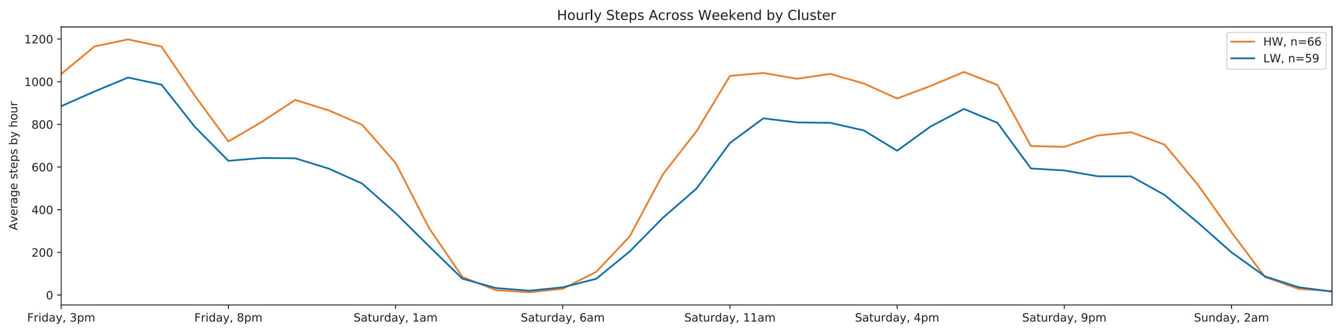

Figure 4: HW and LW clusters average hourly step counts across a weekend [13].

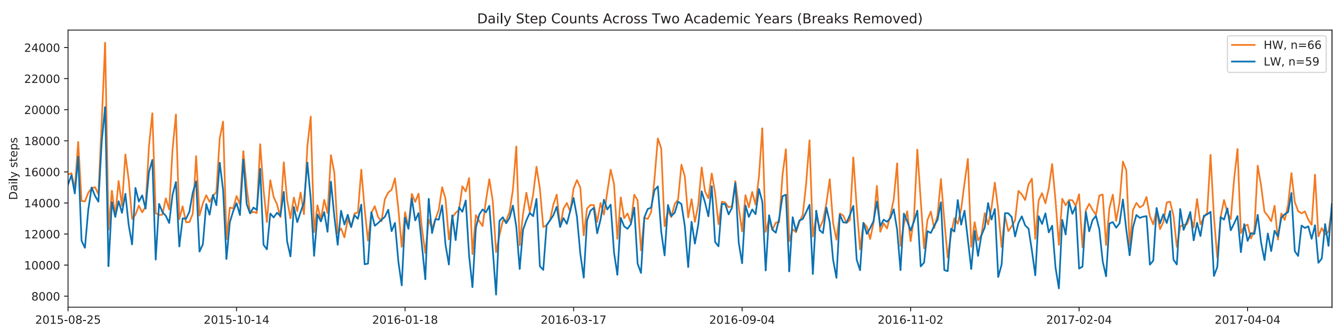

Figure 5: Step clusters over each semester across a time span of two academic years.

Table II: Breakdown of sample by clusters for demographic traits. Percentages are column-wise with respect to gender and race.

demographic	type	HW (n=66)	LW (n=59)
gender	male	40 (60%)	27 (46%)
	female	26 (40%)	32 (54%)
race	white	52 (78%)	31 (52%)
	latino	9 (14%)	12 (20%)
	asian	3 (4%)	9 (15%)
	black	1 (2%)	3 (5%)
	foreign	1 (2%)	3 (5%)

(p = .005) before entering college compared to students in the LW cluster. Results from the Big Five Inventory found HW students to be more extroverted ($p = .009$) and conscientious ($p = .008$) than students in the LW cluster. We also observe HW students noted themselves as more trusting than LW students ($p = .02$) based on the Rosenberg trust assessment [14].

We then examined the four remaining surveys issued after each semester to assess cluster differences throughout two years in college. To account for the repeated measures structure of these surveys, linear mixed effects models were used to analyze the relationship between each survey response and cluster [15]. Survey responses were kept as the dependent variable with repeated measures. We entered cluster as a fixed effect in the model and included intercepts for students as our random effect.

$$\text{surveyResponse}_t = \text{cluster}_t\beta_1 + student_t\gamma + \epsilon_t$$

P-values were obtained by chi-square difference tests of the full model (containing student's cluster) against the reduced model where student's cluster was withheld. To report magnitude differences in responses between clusters, responses were averaged across the four surveys and sepa-

Table III: Significant correlates to weekend cluster of traits and activities before entering college

variable category	variable	$t-$**test** (p)	**change in mean from LW to HW** males	females	point scale
Activities, how frequently do you...	play varsity sports	.004	+28.4%	+10%	5
(higher scores = higher frequency)	play club sports	.005	+18.8%	+6.6%	5
Personality/Self-image	extraversion	.009	no change	+14%	5
(higher scores = more expressive of trait)	conscientiousness	.008	+8%	+1.8%	5
	trust	.02	+3%	+4.4%	5

Table IV: Significant correlates to weekend cluster of traits and activities throughout the first two years of college

variable category	variable	linear mixed effects (p)	**change in mean from LW to HW** males	females	point scale
Activities, how frequently do you...	do an inactive hobby	.03	no change	-12.2%	5
(higher scores = higher frequency)	watch TV	.02	-6.7%	-11.7%	8
	use internet for leisure	.02	no change	-12.8%	8
	listen to music	.006	-6.6%	-16%	8
	exercise with others	.009	+9.4%	+12.8%	4
Personality/Self-image	self-esteem	.007	+3.8%	+7.7%	50
(higher scores = more expressive of trait)	happiness	.008	+5%	+8%	5
	trust	.006	+4.8%	+4%	5
Mental Health	depression	.01	-3.8%	-8.6%	60
(higher scores = higher risk)	anxiety	.03	no change	-9.3%	60
Social Network	number of friends	.03	+2.6	+2.8	10 (mean)
Physical Activity	Fitbit active minutes	.01	+8	+4	40 (mean)

rated by gender. Differences in responses between clusters remained stable across repeated measures i.e., no intersections or significant directional changes unique to a particular cluster were present, suggesting the average response across repeated measures provides an accurate representation of differences between clusters. An overview of these results are provided in Table IV and detailed below. We note that extraversion and conscientiousness do not reappear in Table IV. Personality traits were only assessed in the first and second surveys, leaving only one assessment in the Fall of the students first year to represent two years in college. While personality traits exhibit strong correlations ($\bar{r_s} = .76$, $\sigma = .056$) between the first and second surveys, we refrain from extrapolating this across the two years. We further note that trust remains significant through students time in college, however, we do not observe varsity and club sports to be significant beyond high school.

Returning to activity preferences, LW students were more likely to spend time doing inactive hobbies ($p = .03$) based on a sedentary time scale assessment [16]. As for specific inactive hobbies, questions were modified to reflect on the previous semester, asked in the form of “On a typical day during the current semester, how much time did you spend doing each of these activities?” We observe that LW students spent more time watching TV ($p = .02$), using the internet (specifically for leisure) ($p = .02$) and listening to music ($p = .006$). HW students were more likely to spend time exercising with others ($p = .009$) and tended to exercise longer during a typical session than LW students ($p = .01$). This was measured by the average number of daily active minutes each student received in each of the four semesters. Active minutes are calculated using metabolic equivalents (METs) as these measure energy expenditure and are weight agnostic. Fitbit measures active minutes by periods of 10 minutes or more for which the user maintains a level at or above 3 METs [17]. These four measures of active minutes were then examined using the same mixed effects model structure as the survey responses. Sleep duration from Fitbit data was also examined, however, no significant differences were found between clusters.

With regards to personality and self-image, students completed self-esteem and trust assessments and were asked about their level of happiness based on a five point Likert scale [14], [18]. Findings showed HW students had higher levels of self-esteem ($p = .007$) and happiness ($p = .008$) and were more trusting of others ($p = .006$) compared to LW students. CES-D depression and STAI anxiety screenings showed HW students were also at a decreased risk of depression ($p = .01$) and anxiety ($p = .03$) compared to LW students [19], [20]. Finally, HW students had larger social networks ($p = .03$), averaging two to three more effective social ties than LW students. An effective social tie is defined as a contact in which a communication event (e.g. messaging, phone call) is observed up to time t and which we also know that a future communication event will be observed at $t + 1$ [21]. The number of effective social ties for every student was examined at the end of each semester, testing the four repeated measures in the same manner as the survey responses.

IV. Discussion

Significant differences in step counts occurred only on weekends, an intuitive finding in the context of students on a college campus. During the week, a student's time is restricted by classes and studying whereas during the weekend, a students time is their own. We also found weekend step counts to be a stable trait, referring back to Fig. 4, HW students persistently recorded more steps on weekends over the two academic years compared to LW students.

Based on results from the survey data, we note two sets of factors associated with cluster location: sociability (network size, extraversion, sedentary behaviors, exercising with others) and SWB (self-esteem, happiness, risk of depression and anxiety). For both men and women, sociability was associated with HW and non-sociability, e.g., sedentary activities were associated with LW. Particular indicators of sociability were more pronounced for women and men respectively, but overall, sociable women and men had higher step counts on weekends. We also observe the HW cluster engaged in more physical activity, finding a typical active session to last 5-10 minutes longer than the LW cluster. Given the strong correlation between Fitbit steps and active minutes ($r_s = .8$, $p < .001$), this difference may be the result of HW students gaining more active minutes on the weekend when they are getting in more steps. We also note that from the survey responses, the HW cluster marked they spent more time exercising with others, suggesting exercise may be performed as a social activity among this cohort.

These group differences are consistent with individuals in HW being more active participants on the type of campus culture emphasizing extra-curricular participation in the sort of "party culture" sociological studies reveal is typical of American college campuses [22]. This suggests that integration into the dominant campus culture emphasizing extra-curricular socializing on the weekends may lead to higher SWB. However, higher SWB may also lead students to become more active participants of extra-curricular socializing. While inferring causality is beyond the scope of this paper, prior research reports similar findings, suggesting the correlation between sociability and SWB extends beyond this study [23]–[25]. In this paper, we instead focus on the observation that trends in students weekend step counts correlate with these characteristics, suggesting weekend activity levels could serve as an measurement for informing an individual's SWB.

V. Limitations

We note our sample size as a limiting factor of this study and address the potential selection bias introduced regarding students included in this analysis as opposed to the excluded students, referring back to Table 1. This subset of students was chosen as they had been involved in the study the longest and were the most compliant, therefore having the most data to provide more accurate results. All included students were also measured over their first semester, an important span of time as this is when students are first arriving on campus, forming ties and adjusting to college life. We compared the 125 students included in the study and the 508 who were withheld to ensure our demographics were still reflective of the overall university demographic distributions. We found no significant differences in demographic distributions among age, gender or race.

We also note that given the nature of the NetHealth study, our sample has little variation in age, truncated variation in socioeconomic background and all students are observed in the same environment. As a result, additional studies are necessary across different age groups and backgrounds to validate these findings.

VI. Conclusion

The past decade has seen an increase of research in positive psychology and the nature of subjective well-being. This coinciding with a growing interest in measuring one's self through wearable computing devices offers new behavioral data to be leveraged in its study. In this paper, we clustered weekday trends in step counts from a cohort of 125 college students, resulting in students with high weekend step counts with respect to their average week and those with lower weekend step counts. Weekend differences between clusters persisted throughout the two academic years, suggesting weekend step counts to be a stable trait. Students with higher step counts on weekends were, on average, more sociable and had higher levels of subjective well-being. Given the correlations among these factors, we propose weekend activity be considered as a measure of informing one's subjective well-being.

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