Exercise, Mental Health and Perceptions: Assessing Long-term Physical Activity Changes Using Wearable Fitness Trackers

Abstract

**Background:** The health behaviors young adults develop in college have been shown to have a lasting impact throughout their lives. With the rise in popularity of physical activity trackers, these health behaviors can now be monitored unobtrusively and continuously to provide more accurate representations of students moderate-to-vigorous physical activity (MVPA) patterns.

**Objective:** The objectives of this study were to determine whether participants experience a long-term change in their MVPA and to assess the impact of these changes.

**Methods:** We examine a college cohort of 123 students across two academic years (18 months) using Fitbit Charge HRs. Personal data from surveys administered to students once a semester covered physical and mental health perceptions and activity preferences. A smartphone application allowed social networks to be mapped based on who students communicated with through phone calls and SMS.

**Results:** We observe 41 students who experienced a significant increase in MVPA ($\alpha = .05$) and 44 students who experienced a significant decrease in MVPA ($\alpha = .05$). Increases in MVPA were associated with an improved self-image over time ($P = .01$), while decreases were associated with increased risks of depression and anxiety ($P < .001$). Among the students who decreased in MVPA, students without an alter who decreased in MVPA noticed these changes in their self-reports ($P = .056$), while students with an alter who also decreased in MVPA displayed a null trend in their self-reported MVPA ($P = .30$).

**Conclusions:** Through our assessment of changes in long-term MVPA, we further support the association between exercise and mental health through highly granular, objective measurements of MVPA. We also provide suggestive evidence of an association between one’s self-perception and social network, where an individual may be less likely to perceive changes in their health behaviors if these changes are reflected among their friends. The ability to perceive changes in one’s health behaviors may serve as an important aspect of correcting and promoting these behaviors in a college setting and warrants further study.

**Keywords:** Health; Mental Health; Physical Activity; Exercise; Perception; Social Network; mHealth; Activity Trackers; Fitness Trackers;
Introduction

Motivation
The shift from high school to college presents a major life change for many young adults: entering an unfamiliar environment, cultivating new social ties and finding independence outside of parental guidance [CITATION Hicks2008 \l 1033]. Many behaviors such as healthy choices developed in college have been shown to influence health well into adulthood [CITATION Schmidt2012 \l 1033]. Therefore, this time marks a critical point in development when student’s health behaviors such as physical activity (PA) are being formed; as prior research has well established the benefits of PA [CITATION Warburton2006 \l 1033][CITATION Lee2012 \l 1033].

Daily exercise has been linked to the prevention of chronic diseases including cardiovascular disease, diabetes, cancer, hypertension, obesity, depression, and anxiety [CITATION Warburton2006 \l 1033][CITATION Pate1995 \l 1033][CITATION Janssen2010 \l 1033]. Proper PA can boost the immune system, lower stress levels, and prolong life expectancy [CITATION Lee2012 \l 1033][CITATION Wen2014 \l 1033]. Without these benefits, however, those with more sedentary lifestyles experience more health problems [CITATION Thorp2011 \l 1033]. As such, it is important to ensure that young adults develop healthy behaviors in college given the long-term influence and lasting benefits.

Background
While this notion has received prior attention in the research community, until recently, many studies examining PA relied on subjective measures, with participants reporting their PA habits through surveys. A systematic review of 49 studies was conducted to assess changes in PA from adolescence to early adulthood [CITATION Corder2017 \l 1033]. The studies concluded that a modest decline in PA occurs between adolescence and young adulthood and called for more objective, longitudinal, PA data to better investigate factors associated with changes in PA.

The growing interest in self-monitoring through PA trackers provides this opportunity for personal health to be measured with high granularity and at scale [CITATION Fawcett2015 \l 1033]. The mobility and minimally invasive nature of these wearable devices posit them as ideal tools for long-term monitoring given computing devices such as Fitbits have been shown to provide reliable tracking of PA and reasonable measures of sleep duration [CITATION Diaz2015 \l 1033][CITATION OHare2015 \l 1033].

A recent emphasis has been placed on using such accelerometer data from PA trackers for intervention and observational research on personal health among college campuses. Wearable fitness trackers have been used for intervention-based
studies including obesity prevention and understanding the role of wearables in promoting healthy habits [CITATION Arigo2017 \l 1033 ][ CITATION Kim2018 \l 1033 ]. Though removed from college campuses, a four-year observational study followed students from the 10th grade onward to find patterns of MVPA in the transition from adolescence to adulthood [ CITATION Li2016 \l 1033 ]. Utilizing objective measures for PA, these studies show that without interventions, college students are likely to decline in their MVPA over time, however, assessments were made only intermittently throughout each study rather than continuously.

Objectives
The NetHealth study being conducted at the University of Notre Dame is aiming to capture objective changes in PA among college students through wearable technology [ CITATION Purta2016 \l 1033 ]. Using NetHealth participants, in this paper, we examined a cohort of 123 college students over the course of two years through unobtrusive monitoring using Fitbit Charge HRs. We identified two subgroups from this cohort: one experiencing an increase in MVPA over the two years and the other, a decrease. Using panel data from surveys administered to students once a semester, we examined changes in their survey responses as their MVPA habits change. With SMS data gathered from these students using a smartphone app, we mapped their social networks to understand the role alters play in an ego’s perceptions of their PA over time. In doing so, we further validate existing relationships between MVPA and mental health through highly granular and long-term data and provide novel insights into how social networks may affect an individual’s perception of their own physical activity.

Methods

Study Design
The data comes from the NetHealth study conducted at the University of Notre Dame. All procedures were fully approved by the institutional IRB before distribution. The study features an ongoing collection of demographic, psychometric, social network and physical activity data. Demographic and psychometric data are collected through surveys administered to NetHealth participants once a semester. Social networks are mapped through phone calls and SMS messages recorded via a smartphone app. Finally, the physical activity data measured by Fitbit Charge HRs includes heart rate, METs, steps, calories burned, and minutes asleep.

Figure 1. Consort diagram of NetHealth recruitment and students selected for this analysis in this paper. Asterisks indicate students added as additional alters for ego network analysis.
Recruitment split the cohort across three tiers based on when they entered the study, the process and sample numbers are outlined in Figure 1. 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. The 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.

### Compliance
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 (Figure 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 (19 out of 24 hours) for that day to be considered compliant as this threshold provides a good indication of activity and sleep [CITATION Purta2016 \l 1033]. A distribution of the number of complaint days in each student’s least compliant semester is shown in Figure 2. We focus on students least compliant semester to ensure students selected have a sufficient amount of data in each of the four semesters.

![Compliance Table](image)

<table>
<thead>
<tr>
<th>Tier 1: 391 students entered the study in Aug. 2015, first come first serve basis after demographics were met in keeping with the overall university demographic distributions</th>
<th>Tier 2: 97 students entered the study from Nov-Dec 2015, nominated by existing participants in the study</th>
<th>Tier 3: 210 students entered the NetHealth study in April 2016</th>
</tr>
</thead>
<tbody>
<tr>
<td>391</td>
<td>97</td>
<td>145</td>
</tr>
</tbody>
</table>

Figure 2. Distribution of student’s number of compliant days in their least compliant semester across the four semesters measured.
As seen in Figure 1, approximately 400 students had a semester where this compliance threshold was not met or 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 student’s least compliant semester was 49, approximately \textit{half} of the total days in a semester. One hundred and twenty-three students were above this median of 49 compliant days per semester and were selected as the cohort for our analysis in this paper (Figure 1, level 5). All 123 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 1, with all students ranging between ages 17 and 19. Comparisons were made between the 123 students included in the study and the 508 excluded which we address our \textit{Limitations} section.

Table 1. Comparison of baseline characteristics between Fitbit students included in this analysis versus students excluded based on compliance.

<table>
<thead>
<tr>
<th>Demographic</th>
<th>Included, n = 123</th>
<th>Excluded, n = 510</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>65 (53%)</td>
<td>265 (52%)</td>
</tr>
<tr>
<td>Female</td>
<td>58 (47%)</td>
<td>245 (48%)</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>81 (66%)</td>
<td>335 (65%)</td>
</tr>
<tr>
<td>Latino</td>
<td>21 (17%)</td>
<td>57 (11%)</td>
</tr>
<tr>
<td></td>
<td>12 (9%)</td>
<td>46 (9%)</td>
</tr>
<tr>
<td>-------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td>Asian</td>
<td>12 (9%)</td>
<td>46 (9%)</td>
</tr>
<tr>
<td>Black</td>
<td>4 (3%)</td>
<td>34 (6%)</td>
</tr>
<tr>
<td>Foreign</td>
<td>4 (3%)</td>
<td>38 (7%)</td>
</tr>
</tbody>
</table>

Data
Data spanned the 2015/2016 and 2016/2017 academic years. Seasonal breaks were removed from consideration as compliance issues were most severe during these times and days were not representative of a student’s time on campus [ CITATION Purta2016 \l 1033 ]. This left a time span of eighteen months with nine months per academic year.

Minute-by-minute heart rate data was used for determining students MVPA. As prior studies have shown Fitbit Charge HR trackers to be affected by systematic errors and overestimation of certain heart rate zones, extensive pre-processing steps were taken to account for these errors [ CITATION Gorny2017 \l 1033 ][ CITATION Leininger2016 \l 1033 ].

Data pre-processing
Imputation
We first imputed the data as a user’s heart rate was not always recorded during bouts of MVPA possibly due to moisture interfering with the readings or the band sliding away from the optimal point on the wrist. Artifacts were found in the data corroborating this issue as seen in Figure 3: a student’s heart rate begins to increase at which point data is only collected intermittently and once the recordings steady, the heart rate decreases, suggesting the student’s bout had ended.

Figure 3. Minute-by-minute Fitbit recordings during a bout of elevated heart rate.
To determine the best imputation method, synthetic records of 24 hours were generated which contained the true heart rate values for each minute with chunks of minutes then set as missing for an algorithm to impute, allowing the algorithms to be evaluated.

To ensure the synthetic records were accurate representations, records with missing data were analyzed to determine the most frequent lengths of missing data. One record of daily data was pulled from each student at random which had 20% of its data missing. This threshold was used as no records involved in this analysis had more than 20% of data missing as per our compliance threshold. Each record was then parsed to determine the average length of consecutive minutes that were missing. The majority of missing data lengths ranged from 2 to 25 minutes, however, lengths as high as 150 minutes were also frequent. Given these variations, lengths of 25, 50 and 150 minutes were selected for testing.

Table 2. RMSE of best performing imputation method across various lengths of missing data.

<table>
<thead>
<tr>
<th>Missing data length</th>
<th>Method</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>25 minutes</strong></td>
<td>Kalman arima</td>
<td>10.5</td>
</tr>
<tr>
<td></td>
<td>Linear interpolation</td>
<td>10.9</td>
</tr>
<tr>
<td></td>
<td>Kalman structural time series</td>
<td>10.9</td>
</tr>
<tr>
<td><strong>50 minutes</strong></td>
<td>Linear interpolation</td>
<td>12.3</td>
</tr>
<tr>
<td></td>
<td>Kalman structural time series</td>
<td>12.3</td>
</tr>
</tbody>
</table>
One record with no missing data was then pulled from each student at random. Each of these records was divided into chunks of 25 minutes and chunks were deleted at random until 20% of the data was missing. Several imputation algorithms were then tested on these synthetic records and evaluated using RMSE only on the minutes which were withheld. Consecutive tests conducted using lengths of 50 and 150 minutes to divide the records respectively. Results are provided in Table 2 with linear interpolation providing the best results for lengths of 50 and 150 minutes and comparable results for lengths of 25 minutes. Given the negligible difference in lengths of 25 minutes, we chose linear interpolation for imputing the data.

### Heart Zone Calculation

After imputation, records of minute-by-minute data were processed to determine bouts of MVPA. A bout of MVPA required students to elevate their heart rate to their target heart zone for at least 10 consecutive minutes, a threshold in line with US Department of Health and Human Services physical activity guidelines [CITATION Health2018 \l 1033 ]. While recent work shows bouts of any duration may still result in mortality benefits, we find there is currently more support (and health benefits) for bouts of 10 minutes [ CITATION saint2018moderate \l 1033 ]. To account for any errors in device recording or heart rate falling temporarily outside the target heart zone, any bouts of MVPA separated by a single minute outside the target heart zone were combined.

Total minutes spent in target heart zones were then calculated for each day using the Karvonen formula [ CITATION King1996 \l 1033 ]. While this formula has fallen under scrutiny for its accuracy, given our samples truncated age range and limited resources for more robust measurement, we found this to be the most appropriate method [ CITATION Verschuren2011 \l 1033 ]. The American Heart Association notes the optimal heart rate for one’s target heart zone begins at 50 percent of your maximum heart rate, which we use in the Karvonen formula [CITATION Association \l 1033 ]. We outline the formula for convenience below.

1. Heart rate reserve \((HRR) = max\text{ heart rate } (MHR) – resting\text{ heart rate } (RHR)\)
2. Target heart zone minimum \(\) = \((HRR * .5) + RHR\)

Target heart zones were calculated for each user and for each day to account for potential changes in resting heart rate over the two academic years. Minutes spent within and above a student’s target heart rate zone were then downsampling into daily sums of what we define as target minutes.
Correlations to Fitbit Activity Measures

In comparison to daily aggregates of PA data collected by Fitbit (Figure 4), we find target minutes correlated positively with all Fitbit measures and strongly with Fitbit’s cardio ($r_s = .9$) and peak ($r_s = .7$) heart zone measures which also use the Karvonen formula but do not address missing data [CITATION Fitbit !1033 ]. The strength of these correlations suggests any increase in accuracy afforded by imputation and modifications to heart rate calculation are minimal in this data set.

We observed a minimal correlation between steps and target minutes ($r_s = .1$), likely the result of many students having days with high step counts, but no exercise. To investigate this further, we examined the correlation between steps and target minutes using only days where students target minutes did not equal zero. This modification increased the correlation to .85, from this we can infer that a higher number of target minutes are indicative of a higher number of steps, however, a higher number of steps does not mean a higher number of target minutes.

Trend Analysis

Students target minutes were further down-sampled to the sum of target minutes per month. Each students time series spanned from September 2015 to April 2017 (18 months), with the summer months May, June and July withheld. The sum of each month was then divided by the number of days compliant days in that month, this
was done to account for months with breaks such as December. Trends were then extracted from each time series using additive seasonal decomposition with a frequency of nine to account for the months removed from consideration [ CITATION Cleveland1990 \l 1033 ]. A Mann-Kendall test was then performed on each trend using an $\alpha$ of .05 [ CITATION Mann1945 \l 1033 ]. This determined whether a monotonic upward or downward trend was present in the time series. Among the 123 students examined, 41 featured a significant positive trend (PT) and 44, a significant negative trend (NT), with a remainder of 38 students. An average time series for these trends is visualized in Figure 5.

Figure 5. Average trend for each group from August 2015 to April 2017, includes May, June, and July of 2016, however, these months were withheld from our trend analysis.

Although all students met the appropriate compliance threshold for this analysis, biases in differences for month-to-month compliance could still exist, such as a student having 30% compliance for month A and then 80% compliance for months B and C, resulting in possibly more activity for B and C. To ensure these behaviors did not introduce a bias towards certain trends, distributions of the total compliant days for each trend group were calculated by month. The Kruskal-Wallis H-test was then performed on each month, using an $\alpha$ of .05. No significant results were found, suggesting no bias was present between month-to-month compliance and trend groups [ CITATION Kruskal1952 \l 1033 ][ CITATION Jones2001-- \l 1033 ].

Results

Descriptive Statistics

Students responses across four of the surveys were then examined. The first survey, reflective of student’s senior year in high school, was omitted as Fitbit data collection did not begin until late in the summer of 2015. This left fall 2015, 2016 and spring 2016, 2017 surveys as our panel data. Our focus was to determine whether student’s responses changed over time in accordance with their change in MVPA. Therefore, we focused on within-group methods for analysis, including non-parametric repeated measures ANOVA (Friedman’s test) and Wilcoxon signed-rank test, depending on how frequently each survey question was asked. Any missing survey values were imputed using forward fill to keep the students answers
consistent across the missing responses. Results and respective statistical tests used are outlined in Table 3.

Table 3. Summary of descriptive statistics for MVPA trajectories based on survey responses. The Change column refers to percent difference between the average score for the first and last survey.

<table>
<thead>
<tr>
<th>Positive MVPA Trend</th>
<th>Semesters question was asked</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
<td>Variable</td>
</tr>
<tr>
<td>Activities, how frequently do you... (higher score indicates higher frequency)</td>
<td></td>
</tr>
<tr>
<td>Do an inactive hobby</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Perception/Self-image (higher score indicates a more positive perception)</td>
<td></td>
</tr>
<tr>
<td>Health</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Self-esteem</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Body-image</td>
<td>Friedman’s</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Negative MVPA Trend</th>
<th>Semesters question was asked</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
<td>Variable</td>
</tr>
<tr>
<td>Activities, how frequently do you... (higher score indicates higher frequency)</td>
<td></td>
</tr>
<tr>
<td>Participate in club or sport</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Perception/Self-image (higher score indicates a more positive perception)</td>
<td></td>
</tr>
<tr>
<td>Health</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Level of own activity</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Level of friend’s activity</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Mental health, risk of... (higher score indicates a higher risk)</td>
<td></td>
</tr>
<tr>
<td>Anxiety (BAI)</td>
<td>Friedman’s</td>
</tr>
<tr>
<td>Anxiety (STAI)</td>
<td>Wilcoxon</td>
</tr>
<tr>
<td>Depression (CESD)</td>
<td>Wilcoxon</td>
</tr>
<tr>
<td>Other</td>
<td></td>
</tr>
<tr>
<td>Weight</td>
<td>Friedman’s</td>
</tr>
</tbody>
</table>

We observed that in response to “On a typical day during the current semester, how much time did you spend doing an inactive hobby?,” PT students gave lower marks to this question over time ($P = .03$). These students also gave higher marks in assessments related to their health ($P = .025$), self-esteem [CITATION Rosenberg2015 \ 1033] ($P = .01$), and body-image [CITATION Reboussin2000 \ 1033] ($P = .048$).

As for NT students, they gave lower marks to participation in clubs and sports ($P = .001$), self-reported level of activity [CITATION DeLaHaye2011 \ 1033] ($P = .01$), level of typical friend’s activity ($P = .039$), and health ($P < .001$) over time. CES-D depression screenings [CITATION Radloff1977 \ 1033] showed an increasing risk.
of depression ($P < .001$) coupled with anxiety; based on the BAI ($P = .01$) and STAI ($P < .001$) screenings [CITATION Spielberger2010 \l 1033 ][ CITATION Beck1990 \l 1033 ]. NT students also reported weighing more over time ($P = .003$).

**Network Analysis**

Many of the changes in survey responses corresponded intuitively to the MVPA trend type such as PT students giving higher marks to their health and NT students giving lower marks. A novel observation was that students had systematically different perceptions of whether the level of their typical friend’s physical activity increased or decreased over time based on their membership in the NT group. To further explore the accuracy of these perceptions, we examined the alters of each NT ego network. Of the 44 students with NT labels, 2 students were omitted from this analysis as they had no SMS data.

Given only 123 of the initial 689 NetHealth study participants were selected for this analysis, this reduced the chances of capturing these student’s full ego networks. To compensate for this, we allowed previously excluded students to be reconsidered, but *only as alters* to provide more accurate ego networks for the 42 NT students. Given our survey assessments of activity began in the Spring 2016 semester, we were only interested in whether NT alters MVPA decreased from this semester onward, therefore sufficient compliance was not necessary for Fall 2015.

Compliance restrictions followed the same threshold of *at least 49 compliant days per semester*, however, for Tier 1 and Tier 2 students, Fall 2015 was dropped and for Tier 3 students, the Fall 2015 and Spring 2016 semesters were dropped. Recall that Tier 2 students entered the study toward the end of the Fall 2015 semester and Tier 3 students entered near the end of the Spring 2016 semester. Lessening this restriction added 83 more students to be considered as alters for the NT ego networks. Among these students, 31 were from Tiers 1 and 2 and 52 students were Tier 3.

To avoid any biases, the same method for assigning our initial cohort of 123 students was used for these 83 students. However, instead of using 18 months, Tier 1 and 2 students had 13 months, while Tier 3 students had only 9 months. Of these students, 9 were labeled with a negative trend, while only 2 were labeled with a positive trend, these 11 students came from Tiers 1 and 2, while no Tier 3 students were labeled positive or negative.

With new students added in to provide more accurate ego networks, we limited each NT ego network to their top five strongest ties. The limit of five was chosen to ensure all NT students would have an ego network of the same size and to prevent noise from students with larger networks and weaker ties. The strength of ties was measured using the total number of days two students exchanged SMS messages, with more days indicating stronger ties.
We next examined the number of NT alters in each NT ego network, referring to Figure 6, we observed 17 NT students with no NT alter among their top five strongest ties, 24 NT students had one or two NT alters, and 3 NT students had three to four NT alters. To determine whether NT students accurately perceived their friends level of activity to be decreasing, we partitioned the NT students into two groups: those with and those without NT alters.

**Figure 6. Distribution of NT alters in NT student’s ego networks.**

Returning to the survey responses, we observed that NT students with NT alters perceived a decrease in their friend’s level of activity (Friedman’s, $P = .027$) while NT students without NT alters did not perceive a significant decrease (Friedman’s, $P = .21$). We next compared the two groups on the perceived level of their own PA and observed NT students with NT alters did not perceive a significant change in their activity (Friedman’s, $P = .31$) and students without NT alters also did not perceive a significant change (Friedman’s, $P = .056$). We provide a complete representation of these comparisons in Figure 7.

**Figure 7. Comparison of perceived levels of own and typical friends activity between NT students with NT alters and NT students without NT alters.**
Discussion

Principal Findings

The aim of this analysis was to assess whether students in a college setting changed their MVPA habits over time and if so, assess the impact of these long-term changes. Among the 123 students selected for this analysis, 85 students were observed to experience a significant change in their MVPA habits based on their Fitbit data over two academic years, with 41 students increasing in MVPA overtime and 44 decreasing.

Heart rate data were used to capture when these students were performing MVPA. We favored this metric over steps as steps are a widely involuntary measure of one’s PA. There are many factors which may influence a student’s steps over time, especially given a college environment where each student’s daily schedule changes each semester, thereby changing their daily routine. Even the 10,000 steps per day goal has fallen under scrutiny since it does not guarantee meeting guidelines to confer health benefits given it does not address intensity and bout length [CITATION Slaght2017 \cite{1033}]. Instead, assessing when students entered their target heart rate for an extended period of time provided a more reliable measure of MVPA. We also observed the Spearman correlation between steps and target minutes was minimal at .1, however, when conditioned on only days where a student exercised, this correlation increased to .85. From this, we can infer that more target minutes in a day, on average, means more steps, however, more steps in a day does not always mean more target minutes.

Moving to the latter aim for this study, we observed from student’s survey responses that PT students improved in their perception of their self-image overtime with better health ($P = .025$), self-esteem ($P = .01$), and body-image ($P = .048$). NT students decreased in their perception of their health ($P < .001$) and increased in risk of anxiety ($P < .001$) and depression ($P < .001$) as well as their weight ($P < .003$).
While many of these relationships have been found in previous works, they provide validity to our method of capturing MVPA trends and show these associations persist when using objective measurements of MVPA [CITATION Wu2015 \l 1033] [CITATION Phillips2015 \l 1033] [CITATION Holstila2017 \l 1033]

We also observed a novel finding in that NT students also perceived the level of their typical friend’s activity to decrease over time ($P = .039$). Splitting the NT students into two groups, we observed that NT students with an NT alter retained this perception of their friends decreasing in activity ($P = .027$) while students without an NT alter did not ($P = .21$). However, NT students with an NT alter did not notice a significant decrease in their own activity ($P = .39$) and the same held for those without an NT alter ($P = .056$). Although insignificant at an $\alpha$ of .05, this observation provides evidence for further study given the level of significance at our sample size. Previous work has shown individuals to be able to accurately perceive their level of fitness [CITATION Simonavice2015 \l 1033]. However, if an ego and its network change a behavior over time, that ego may be less likely to notice the change in their own behavior compared to an ego whose network is not exhibiting a similar change.

**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 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 123 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 between our sample and the students excluded.

Not all questions asked of students were present in each survey, some questions were only asked in certain waves to prevent the surveys from extending beyond a reasonable duration for completion which otherwise may cause students to provide less accurate answers. We also note that given the nature of the NetHealth study, our sample has minor variation in age, truncated variation in socioeconomic background and all students are observed in the same environment. Finally, while many within-study ties exist among students in the NetHealth study, we are unable to capture any MVPA changes among an ego’s ties to students outside the study, prohibiting a complete representation of MVPA changes throughout an ego network. As a result, additional studies are necessary across different age groups and backgrounds to validate these findings.
Conclusions
The physical activity habits formed by college students can have a lasting impact on their lives. With the introduction of physical activity trackers such as Fitbit, these habits can be measured objectively and over long periods of time in an unobtrusive manner. In this paper, we observed 123 students over two academic years finding 41 students who increased in their MVPA overtime, while 44 decreased. Increases in MVPA were associated with improved health perceptions, including self-esteem and body-image, while decreases were associated with increased risk of depression/anxiety and worsened health perceptions. A novel observation was that students who decreased in MVPA perceived their friends level of activity to decrease over time. Further analysis led to the suggestion that individuals perceive their health behaviors in relation to their social networks: if an individual’s health behaviors are changing in parallel with their ego network, they may be less likely to notice the change compared to an individual whose network is not changing or changing in a different direction. The likelihood of an individual correcting this behavior as a result of perceiving it, however, remains to be addressed but could serve as an important aspect of correcting and promoting healthy behaviors in a college setting.

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Conflicts of Interest
None declared.

Abbreviations
PA: physical activity
MVPA: moderate-to-vigorous intensity physical activity
PT: positive trend
NT: negative trend

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