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Patterns of behavior change in students over an academic term: A preliminary study of activity and sociability behaviors using smartphone sensing methods

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ABSTRACT

The recent arrival of smartphone-sensing methods has made it possible to objectively track consequential everyday health-related behaviors rather than rely on self-reports. To evaluate the viability of using sensing methods to monitor such behaviors in detail, the present research used a smartphone-sensing application to describe the patterns of stability and change that characterize a cohort of students' activity and sociability behaviors over the course of a 10-week academic term. Data were collected from 48 students using a smartphone-sensing application, *StudentLife*, which was designed to track daily durations of activity (via the accelerometer sensor) and sociability (via the microphone sensor). Results showed stability estimates were moderate to high for activity ($r_{mean} = 0.66$) and sociability ($r_{mean} = 0.72$) across the 10 weeks. Students started the term with generally healthy levels of activity ($M = 1.87$ h) and sociability ($M = 4.99$ h), which then dropped (activity by 0.42 h, sociability by 0.90 h) over the first half of the term (i.e., before midterm exams). Over the second half of the term, activity levels did not change but sociability increased (by 0.88 h). Students' ethnicity and academic class predicted variation in the activity and sociability trajectories. Discussion focuses on the implications of our results for designing mHealth interventions to address consequential student outcomes (e.g., mental health, physical health).

1. Introduction

People engage in a range of routine everyday behaviors that have a significant impact on their health. Two such behaviors, highlighted in the health-research literature as major components of a healthy lifestyle, are engaging in physical activity on a regular basis (e.g., Maher et al., 2013; Warburton, Nicol, & Bredin, 2006) and being socially connected to others (e.g., Cohen, 2004; Shankar, McMunn, Banks, & Steptoe, 2011). A substantial body of research demonstrates that many students experience problems in these behavior domains during the course of their higher education (e.g., physical inactivity, loneliness; American College Health Association, 2012; Douglas et al., 1997; Keating, Guan, Piñero, & Bridges, 2005; Mounts, Valentiner, Anderson, & Boswell, 2006). One potential solution to addressing this problem is the development of mobile-health (mHealth) applications to help students improve their health-related behaviors (e.g., Gowin, Cheney, Gwin, & Franklin Wann, 2015; Miller, Chandler, & Mouttapa, 2015). Technological improvements in behavioral assessment using sensors embedded in smartphones have paved the way for mHealth interventions that promote behavior-change at scale (Harari et al., in press; Lathia et al., 2013). However, the technological advances in mHealth have outpaced research on how to implement them effectively (Nilsen, Riley, & Heetderks, 2013). Descriptive research charting the behavioral patterns of students could help target periods of the academic term where mHealth interventions could

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most effectively be deployed to promote healthy levels of activity and sociability. Thus, descriptive research is needed to identify critical periods of normative behavior change during an academic term, and whether there is individual variability in the behavior-change patterns.

1.1. Physical activity behaviors

Health guidelines recommend that students get 2.5 hours of physical activity per week (American College Health Association, 2012). Yet, cross-sectional (Douglas et al., 1997; Keating et al., 2005) and longitudinal (Racette, Deusinger, Strube, Highstein, & Deusinger, 2008) survey studies suggest that many students are physically inactive (estimates range from 30% to 50%). In particular, members of ethnic minorities and older students seem to engage in less physical activity during college than do Caucasian students and younger students (Buckworth & Nigg, 2004; McArthur & Raedeke, 2009). The research to date indicates that the college experience may have a negative impact on students' physical activity but provides only a crude estimate of how such patterns might unfold from week-to-week during a term. Moreover, a meta-analysis of studies on college students' activity behaviors found that many studies used subjective and inconsistent measures of physical activity (Keating et al., 2005), such as self-reports of exercising behaviors or more general activity behaviors (e.g., walking, running), not actual duration of time spent in active movement. Thus, research is needed using objective activity measures, both to plot the normative trajectories of activity levels over time and to identify potential socio-demographic predictors of different activity trajectories.

1.2. Sociability behaviors

Sociability has been defined as a preference for affiliating and being with others (vs. being alone; Cheek & Buss, 1981). Most studies of students' sociability behaviors tend to focus on problematic socializing behaviors, such as binge drinking, drug use, and risky sexual behavior (e.g., Raynor & Levine, 2009). However, the health literature lacks a general understanding of students' general sociability behavior as indexed by the amount of time they spend affiliating with others. There is some debate about the importance of general sociability as a health risk factor, with some researchers claiming that sociability can serve as health buffer (e.g., via a sense of social support; Cohen, 2004), and others claiming that the importance of sociability has been overestimated (Friedman, 2000). In addition, studies that have examined students' sociability tend to use self-report methods that tap into students' sociability-related self-views (e.g., "I like to be with people"; Cheek & Buss, 1981; Mounts et al., 2006), but not actual duration of time spent affiliating with others. Relatively few studies have focused on objectively assessing students' sociability over time. Those that have, suggest that active socializing behaviors (e.g., talking to others) are highly stable over a 4-week period (test-retest reliability of $r = 0.63$), and account for about a third of students' waking hours (Mehl & Pennebaker, 2003). Although previous research suggests students generally retain their relative ranking in their sociability behaviors, it is unclear whether sociability trajectories change (increase or decrease) during an academic term and whether such changes are associated with students' socio-demographic characteristics.

1.3. Objectives of the present research

Past research on students' activity and sociability has focused on major milestones and broad patterns, such as behavior change during the transition to college or across the four years of college, but little is known about how these behaviors manifest and change on a more nuanced level (e.g., from week-to-week during an academic term). Moreover, it is unclear whether all students experience similar behavioral changes over a term (i.e., show normative changes in their behavior trajectories), or whether students vary in their behavior change patterns (i.e., show individual differences in their behavior trajectories). One reason for the field's focus on broad patterns is the difficulty associated with studying fine-grained patterns of behavior in the real world. As a result of these difficulties, most behavioral research has focused on lab-based proxies of real-world behavior or self-reports of behavior, both of which are subject to range of biases and limitations (Baumeister, Vohs, & Funder, 2007; Block, 1989; Funder, 2001; Furr, 2009; Paulhus & Vazire, 2007). However, recent advances in mobile-sensing technology have revolutionized behavioral assessment by permitting unobtrusive, continuous tracking of behaviors via mobile sensors (e.g., accelerometers, microphones) embedded in smartphones (Gosling & Mason, 2015; Harari et al., in press; Lane et al., 2010; Miller, 2012).

To examine the viability of using mobile-sensing methods to obtain daily estimates of students' behavioral lifestyles, we present a preliminary study using a smartphone-sensing application to objectively measure students' naturally occurring activity and sociability behaviors over the course of a 10-week academic term. In doing so, we address a gap in the existing mHealth literature by providing a descriptive account of the fine-grained patterns of stability and change that characterize students' health-related behaviors during an academic term. We also examine the socio-demographic predictors of students' behavior trajectories, focusing on the characteristics of ethnicity and academic class. Based on past research on this topic, we expected ethnicity and academic class to predict variation in the activity trajectories, such that ethnic minority members and older students would exhibit lower levels of physical activity than would majority members and younger students. We had no expectations regarding the associations between socio-demographic characteristics and the sociability trajectories. We focus on activity and sociability behaviors with the aim of identifying periods in the academic term when mHealth interventions for students may be targeted most effectively. To do so, we estimate (1) the stability of the behaviors across weeks during the term; and use latent growth curve models to examine (2) the patterns of normative and individual-level change in the behaviors across weeks of the term; and (3) the socio-demographic predictors of the observed behavior trajectories.

2. Method

2.1. Participants and procedure

Participants were recruited from a convenience sample of students enrolled in a computer science course at Dartmouth College. The students were informed that participation was voluntary, and that everyone in the course (including those who elected to not participate) would be permitted to use an anonymized subset of the resulting dataset for use in a class project. Forty-eight students volunteered to take part in the study (38 male, 10 female; 30 undergraduates, 18 graduate students). The study lasted a full spring term – 10 weeks – from March to May of 2013. Additional information about the study design and initial results from the study can be found in Wang et al., 2014 and Wang, Harari, Hao, Zhou, & Campbell, 2015.

Participants were informed about the purpose of the study during an entrance interview, before they filled out consent forms. During the entrance interview, they were told that the study aimed to understand the behavioral patterns that are associated with college student well-being. The participants were given Android phones to use for the duration of the study and were asked to carry the Android device with them at all times for the 10 weeks of the term. They were given an opportunity to ask any questions and were then asked to sign consent forms and complete a battery of questionnaires. The Android phone had the *StudentLife* smartphone sensing application pre-installed (Wang et al., 2014). Among other things, *StudentLife* captured physical activity and sociability behaviors by tracking duration of activity (from the accelerometer sensor) and duration of ambient conversation (from the microphone sensor; described in more detail in the Measures section below). Students' activity and ambient conversation were tracked for 66 days, from the start of the term (which fell on a Wednesday) through the end of the term (on a Friday).

2.2. The smartphone sensing system

The StudentLife system consisted of three main components: automatic and continuous sensing, behavioral classification, and cloud storage (for a detailed, technical description of the system architecture, see Wang et al., 2014). StudentLife assessed participants' behaviors by sampling from a series of sensors: the accelerometer, microphone, ambient light sensor, and phone usage logs (automatic and continuous sensing). StudentLife ran a series of classifiers on the sensor data, in real-time on the phone to infer user behavior (behavioral classification). The behavioral inferences were stored on the phone until the phone was charging and connected to WiFi. When the phone was connected to WiFi, StudentLife uploaded the inference data to a cloud server using an SSL encryption. The data were stored in the cloud server and extracted for analysis (cloud storage).

2.3. Measures

2.3.1. Questionnaires

Socio-demographic characteristics were measured by asking participants to self-report their sex (38 males, 10 females), ethnicity (2 African American, 23 Asian, 23 Caucasian), and academic class (30 undergraduate students, 18 graduate students). Given the preponderance of Asian students, ethnicity was classified as Asian or Non-Asian; we dummy-coded the ethnicity variable with Non-Asian as the reference group to facilitate ease of interpretation and discussion regarding the effects of ethnic minority status on the behavior trajectories. Academic class was coded as a continuous variable, which ranged from 1 (*freshman student*) to 5 (*graduate student*).

2.3.2. Processing the sensor data

To assess activity and sociability behaviors, the daily duration (in minutes) of time spent moving (activity) and in proximity to conversation (sociability) were inferred from the sensor data collected from participants' smartphones. The daily physical activity and sociability estimates were based on features that were extracted from continuous measurements of accelerometer and microphone sensor data. Thus, we could expect users to have up to 24 hours of sensor data on any given day during the study.

To ensure the daily durations we computed were reliable estimates of the participant's behavior for each day, we created a threshold for the minimum number of hours of data needed per day (15 hours). This threshold was used in the data-cleaning process to identify and remove any days with an invalid amount of data. We then aggregated the 66 days for each behavior across days of the week (Sunday - Saturday), so that 10 individual weekly scores for activity and sociability were computed per participant. Below we describe how each of the behavioral dimensions was assessed from participants' sensor data.

2.3.3. Activity behavior

The activity classifier we used was developed in prior work (Lane et al., 2011; Lu et al., 2010) in which it achieved 92–95% accuracy at classifying accelerometer data into activity-based behavioral inferences (i.e., stationary, walking, or running). The activity classifier generated activity inferences based on the accelerometer sensor data every 2 seconds (Wang et al., 2014). To conserve battery life, the accelerometer was sampled every third minute (on for 1 min, off for 2 min); however, when activity was detected, the classifier stayed on until stationary inferences were recorded. To compute the activity durations, we collapsed across all non-stationary inferences (i.e., walking and running) to create a more general activity estimate that captured daily duration of activity. Our activity estimates were based on a mean of 44.91 days ($SD = 18.15$) of accelerometer data per participant (see Table 1 for descriptive statistics).

2.3.4. Sociability behavior

The audio classifier we used to measure sociability was developed in prior work (Lane et al., 2011; Rabbi, Ali, Choudhury, & Berke, 2011) in which it achieved 84–94% accuracy at classifying microphone data into audio-based inferences (i.e., silence, noise, voices). The microphone sensor on participants' smartphones was sampled every third minute (on for 1 min, off for 2 min) and an audio classifier was applied on-the-phone to infer users' duration of time spent around other voices (vs. silence or noise; Wang et al., 2014). When ambient conversation was detected, the classifier stayed on until the conversation was over. The content of conversations was never recorded. Instead, the *StudentLife* application saves the behavioral inference variables of 0 for silence, 1 for noise, 2 for voices, and 3 for unknown. We used these behavioral inferences to aggregate our data into duration of time spent proximal to human speech (either in conversation or around conversation) for each day of the study. This behavioral estimate captures a unique aspect of sociability - the general tendency to affiliate with others as indexed by the amount of time students spend around ambient conversation. Our sociability estimates were based on a mean of 47.67 days ($SD = 16.01$) of microphone data per participant (see Table 1 for descriptive statistics).

3. Results

3.1. Rank-order stability of activity and sociability behaviors

To assess rank-order stability, we computed test-retest correlations between the observed behavior durations for adjacent weeks (e.g., Week 1 and Week 2, Week 2 and Week 3, etc.). As shown in Table 1, stability coefficients for the two behaviors showed that students' behaviors were characterized by a high degree of stability over the 10-week period. The stability coefficients were moderate to high, ranging from 0.42 to 0.77 for activity ($r_{mean} = 0.66$), and from 0.63 to 0.80 for sociability ($r_{mean} = 0.72$). The results from the test-retest correlations indicate that the estimates of weekly activity and sociability were highly stable over time among the students in this sample.

3.2. Mean-level change in activity and sociability behaviors

To get an initial sense of the mean-level change in behaviors over the term, we plotted the means for physical activity and sociability across the ten weeks (Fig. 1A–B). Both behaviors showed a decreasing trend leading up to or during the midterm examination

Table 1
Descriptive statistics and test-retest correlations for activity and sociability behaviors.

	N	*M*	*SD*	WK1	WK2	WK3	WK4	WK5	WK6	WK7	WK8	WK9	WK10
Activity													
WK 1	39	1.81	1.05	–									
WK 2	45	1.87	0.92	0.70**	–								
WK 3	44	1.68	0.78	0.66**	0.74**	–							
WK 4	45	1.53	0.76	0.54**	0.58**	0.61**	–						
WK 5	45	1.44	0.75	0.49**	0.47**	0.45**	0.77**	–					
WK 6	43	1.43	0.77	0.51**	0.66**	0.48**	0.75**	0.74**	–				
WK 7	42	1.56	1.03	0.37*	0.54**	0.71**	0.53**	0.48**	0.42*	–			
WK 8	42	1.47	0.75	0.42*	0.54**	0.54**	0.56**	0.57**	0.69**	0.65**	–		
WK 9	37	1.27	0.76	0.28	0.48**	0.53**	0.52**	0.46**	0.62**	0.72**	0.72**	–	
WK 10	33	1.28	0.70	−0.02	0.08	0.00	0.23	0.24	0.25	0.33	0.49**	0.59**	–
Sociability													
WK 1	41	4.77	2.08	–									
WK 2	46	5.07	1.99	0.80**	–								
WK 3	46	4.58	2.00	0.65**	0.77**	–							
WK 4	46	4.5	2.08	0.70**	0.69**	0.79**	–						
WK 5	46	4.46	1.84	0.57**	0.63**	0.71**	0.79**	–					
WK 6	44	4.37	2.12	0.57**	0.65**	0.57**	0.50**	0.65**	–				
WK 7	43	4.23	2.16	0.49**	0.65**	0.68**	0.68**	0.74**	0.63**	–			
WK 8	43	4.23	2.02	0.64**	0.71**	0.68**	0.71**	0.57**	0.63**	0.77**	–		
WK 9	37	4.48	2.16	0.57**	0.56**	0.67**	0.65**	0.61**	0.52**	0.66**	0.68**	–	
WK 10	33	5.67	2.52	0.21	0.39*	0.42*	0.41*	0.28	0.18	0.39*	0.50**	0.63**	–

Note. *N* denotes the number of students with data for each variable and week. *M* denotes the mean duration of the behavior for each week in hours. *SD* denotes the standard deviation of the behavior duration for each week in hours. WK denotes the week in the term.
**p < 0.01; *p < . 05.

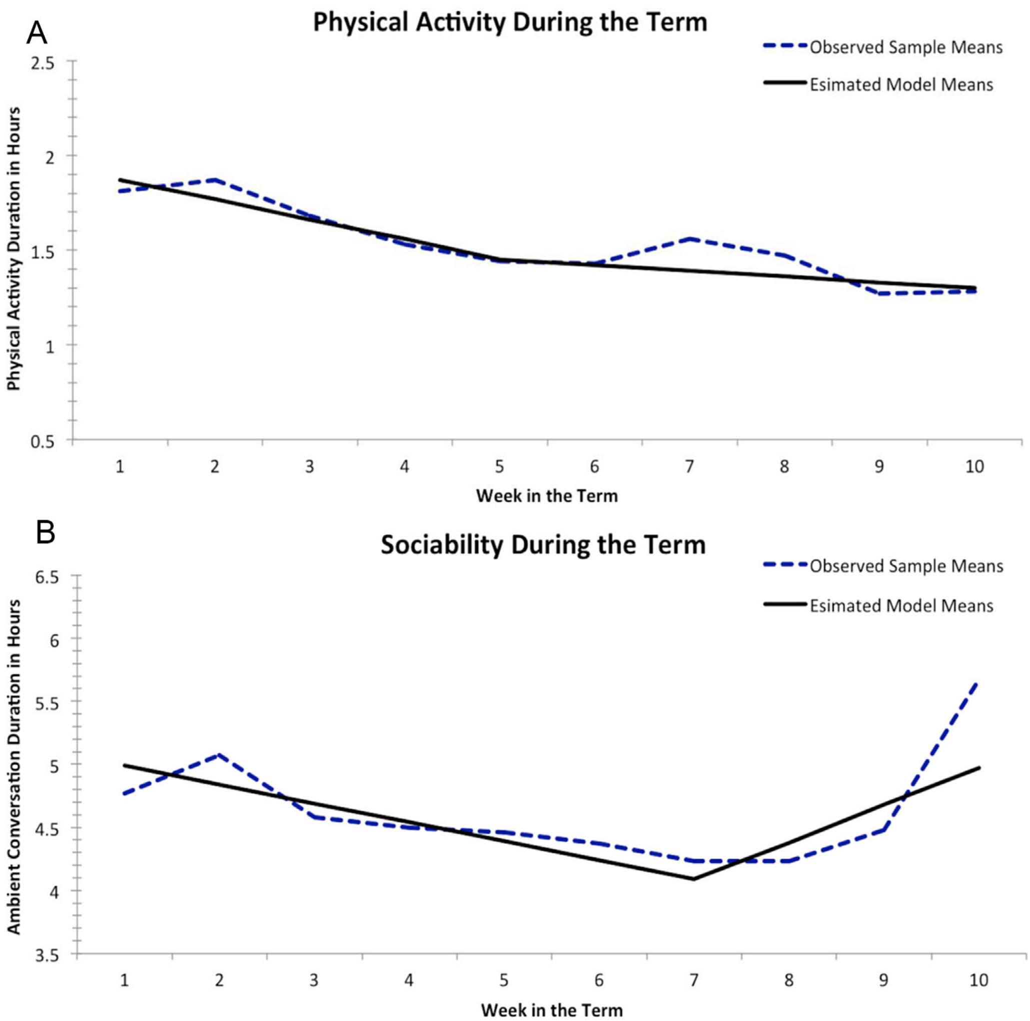

Fig. 1. A. Sensed physical Activity duration over the term – observed and estimated means. B. Sensed sociability duration over the term – observed and estimated means.

period (Weeks 5–7), suggesting piecewise linear regressions with 1 knot (at the beginning and end of the midterm period) might fit the data well. More specifically, the mean levels of physical activity plotted in Fig. 1A depict a relatively linear pattern, in which activity decreases from Week 1–5 (before midterms), shows a slight increase from Week 6–7, and generally decreases from Week 8–10 (after midterms). Fig. 1B plots the sociability means, pointing to a possible quadratic pattern, in which sociability decreases from Week 1–7 (before and during midterms) and increases from Week 8–10 (after midterms). The piecewise approach allowed us to describe the changes in behavior during the term using two latent slopes to estimate the changes before and after the midterm period (a normatively shared event) as our point of reference.

3.2.1. Latent growth curve description

We utilized latent growth curve (LGC) models to model the mean-level and individual-level changes of each behavior over the 10-week academic term (Bollen & Curran, 2006). LGC models provide estimates for latent variables that represent the observed variables (i.e., the activity and sociability behavior durations for each of the 10 week variables). We used MPlus 7 to fit the LGC models with maximum likelihood estimation for activity and sociability. Overall model fit for each unconditional model was assessed by the root-mean-square error of approximation (RMSEA) and its 90% confidence intervals, and the CFI/TLI estimates. Acceptable model fit is indicated by RMSEA values and confidence intervals between 0.00 and 0.08, and CFI/TLI values above 0.90. We used the chi-square difference test to compare nested models and determine whether models with more parameters fit better than more restrictive models. These analyses allowed us to explore how each behavior changes over the term separately.

Overall, our results indicate that each of the behaviors could be fitted with a piecewise linear model with 1 knot during the midterm period (Weeks 5–7). This piecewise approach allowed us to estimate 3 latent variables of interest: Level (the initial behavior duration at Week 1), Slope 1 (the rate of change before midterms), Slope 2 (the rate of change after midterms). To capture the change before and after midterms, Slope 1 was centered at Week 1 and Slope 2 was centered at one of the midterm weeks. We selected the midterm weeks based on the visual examination of the mean plots, resulting in knots at the start (Week 5 for physical activity) and end (Week 7 for sociability) of the midterm period, respectively. We centered these slopes by setting the coefficients to 0. To estimate the change in the weeks before midterms, we set linear coefficients for each week before the knot (e.g., for the activity model we set Week 1 at 0, Week 2 at 1, Week 3 at 2, Week 4 at 3, and Week 5 at 4). To estimate the linear change in the weeks after midterms, we set linear coefficients for each week after the knot (e.g., for the activity model we set Week 5 at 0, Week 6 to 1, Week 7 to 2, Week 8 to 3, Week 9 to 4, and Week 10 to 5).

For each behavior, we tested whether a model with freed residual variance fit the data significantly better than a model with residual variances constrained to be equal. The results for the physical activity model suggest that a model with freed residual variances (RMSEA = 0.11, 90% CI [0.06, 0.16], CFI = 0.90, TLI = 0.91) showed considerable improvement in terms of model fit ($X^2_{change}(9) = 25.89$, $p = 0.00$), compared to a model with constrained residual variances (RMSEA = 0.13, 90% CI [0.09, 0.17], CFI = 0.84, TLI = 0.87). In addition, modification indices suggested that the residual variances for Week 3 and Week 7 be allowed to covary ($r = 0.23$, $p < 0.01$), which resulted in considerable improvement in terms of model fit ($X^2_{change}(1) = 13.89$, $p = 0.00$; RMSEA = 0.08, C.I. [0.00, 0.14], CFI = 0.95, TLI = 0.95). The results for the sociability model suggest that a model with constrained residual variances fit the data well (RMSEA = 0.08, 90% CI [0.00, 0.13], CFI = 0.95, TLI = 0.96) and provided a more parsimonious fit ($X^2_{change}(9) = 12.00$, $p = 0.21$), compared to a model with freed residual variances. In addition, modification indices suggested that the residual variances for Week 4 and Week 6 be allowed to covary ($r = -0.54$, $p < 0.01$), which resulted in considerable improvement in terms of model fit ($X^2_{change}(1) = 8.00$, $p = 0.00$; RMSEA = 0.06, C.I. [0.00, 0.12], CFI = 0.97, TLI = 0.98). The left columns of Table 2 refer to the growth-model fit indices, which show the unconditional and conditional piecewise linear models fit the data well for each of the behaviors. The unconditional model path diagrams with the estimated coefficients for activity and sociability are presented in Figs. 2 and 3.

In the next section we describe the observed patterns of change for the unconditional models for physical activity and sociability. First, we describe the initial level of each behavior at the start of the term (Week 1). The unconditional-model entries in Table 2 present the level mean and level variance. The mean of the level represents the average duration for the behavior at Week 1. The variance of the level represents the amount of between-individual variability for the behavior at Week 1. Significant level variation would indicate that there are differences between individual levels at the start of term that may be explained by other factors. We examine whether students' socio-demographic characteristics are associated with the level variation.

Next, we describe how the behavior changes over the term. The unconditional model entries in Table 2 also present the slope means and variances. The mean of Slope 1 represents the average slope for the behavior prior to midterms. The mean of Slope 2 represents the average slope for the behavior post midterms. The variances of the slopes represent the amount of between-individual variability that exists for the behavior change during these time periods. Significant slope variation would indicate that there are differences between individuals in the rates of change over the term that may be explained by other factors. We also examine whether students' socio-demographic characteristics are associated with the slope variation.

Finally, we examine whether the rate of change in one latent variable is related to the rate of change in another latent variable. Correlations were computed for each of the latent variables (level and slopes) with significant between-individual variability. This step allows us to explore, for example, whether an individuals' behavior duration at the start of the term (Week 1) is associated with their rate of change before or after midterms.

3.2.2. Activity

To examine whether there was an average activity trajectory during the academic term, we fit a piecewise unconditional model with two slopes and a knot at Week 5. The mean level of activity at Week 1 was 1.87 hours, with significant between-individual variation (see top section of Table 2 for coefficients). The slope means indicate that students showed substantial mean-level decreases prior to midterms (Slope 1). However, there was no significant mean-level change post midterms (Slope 2), suggesting that students' activity did not show a normative increase or decrease during this period. Slope variances were significant for both Slope 1 and Slope 2, indicating between-individual variation in rates of activity change before and after midterms. To determine whether the rate of change in one latent physical activity variable was related to the rate of change in another, we correlated the latent variables with one another. A significant negative correlation was found between Level and Slope 1 ($r = -0.09$, $p < 0.05$), suggesting that individuals with higher physical activity duration at the start of term also decreased at a slower rate prior to midterms.

Table 2
Unconditional and conditional latent growth curve models for activity and sociability behaviors.

	Model fit			Level: Intercept at Week 1		Slope 1: Prior to midterms		Slope 2: Post midterms	
	RMSEA [C.I.]	CFI	TLI	*M (SE)* *B(SE)*	σ^2 (SE) β	*M (SE)* *B(SE)*	σ^2 (SE) β	*M (SE)* *B(SE)*	σ^2 (SE) β
Activity									
Unconditional model	0.08 [0.00, 0.14]	0.95	0.95	1.87^{**}(0.14)	0.70^{**} (0.19)	-0.11^{**} (0.03)	0.03^{**} (0.01)	−0.03 (0.02)	0.01^{**} (0.01)
Asian	0.08 [0.00, 0.13]	0.94	0.94	−0.79 (0.25)	-0.49^{**}	0.15 (0.06)	0.53^{**}	0.00 (0.05)	−0.02
Academic class	0.09 [0.00, 0.14]	0.94	0.94	−0.25 (0.12)	-0.33^{*}	0.03 (0.03)	0.17	0.02 (0.02)	0.19
Sociability									
Unconditional model	0.06 [0.00, 0.12]	0.97	0.98	4.99^{**} (0.28)	3.01^{**} (0.76)	-0.15^{**} (0.04)	0.04^{*} (0.02)	0.29^{*} (0.13)	0.51^{**} (0.18)
Asian	0.08 [0.00, 0.13]	0.95	0.95	−1.66 (0.51)	-0.47^{**}	−0.04 (0.09)	−0.10	−0.14 (0.27)	−0.09
Academic class	0.08 [0.00, 0.13]	0.95	0.95	−0.72 (0.22)	-0.48^{**}	0.00 (0.04)	0.02	−0.07 (0.12)	−0.11

Note. Asian = Asian ethnicity coded as 1, Non-Asian ethnicity coded as 0 reference group.
Academic class is coded as 1 = freshman student thru 5 = graduate student.
M = the mean for the latent variables Level, Slope 1, and Slope 2 of the unconditional models.
σ^2 = the variance for the latent variables Level, Slope 1, and Slope 2 of the unconditional models.
B (SE) = the unstandardized beta coefficient and standard error of the conditional models.
β = the standardized beta coefficient of the conditional models.
$^{**}p < 0.01$; $^{*}p < .05$.

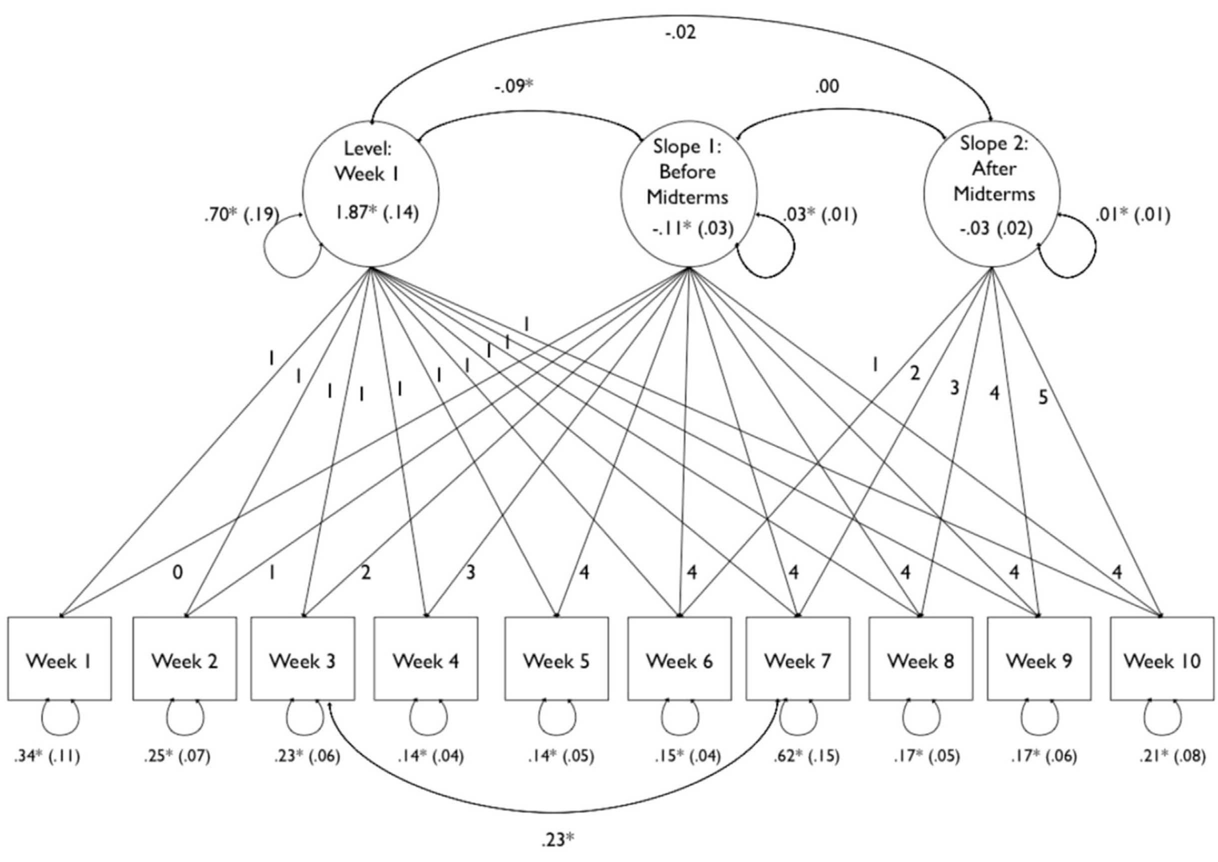

Fig. 2. Unconditional growth curve model for physical activity during academic term. $^{*}p < .05$

3.2.3. *Sociability*

To examine whether there was an average sociability trajectory during the academic term, we fit a piecewise unconditional model with two slopes and a knot at Week 7. The mean level of sociability at Week 1 was 4.99 hours, with significant between-individual variation (see bottom section of Table 2 for coefficients). The slope means indicate that students showed substantial mean-level decreases prior to midterms (Slope 1) and increases post midterms (Slope 2). Slope variances were significant for both Slope 1 and Slope 2, indicating between-individual variation in rates of change during the term. We found no significant correlations between the latent variables for sociability, indicating that sociability levels at the start of the term were not associated with changes during the term.

3.3. *Predicting the behavior trajectories from socio-demographic characteristics*

To examine the associations between socio-demographic characteristics and students' behavior trajectories, we fit a series of

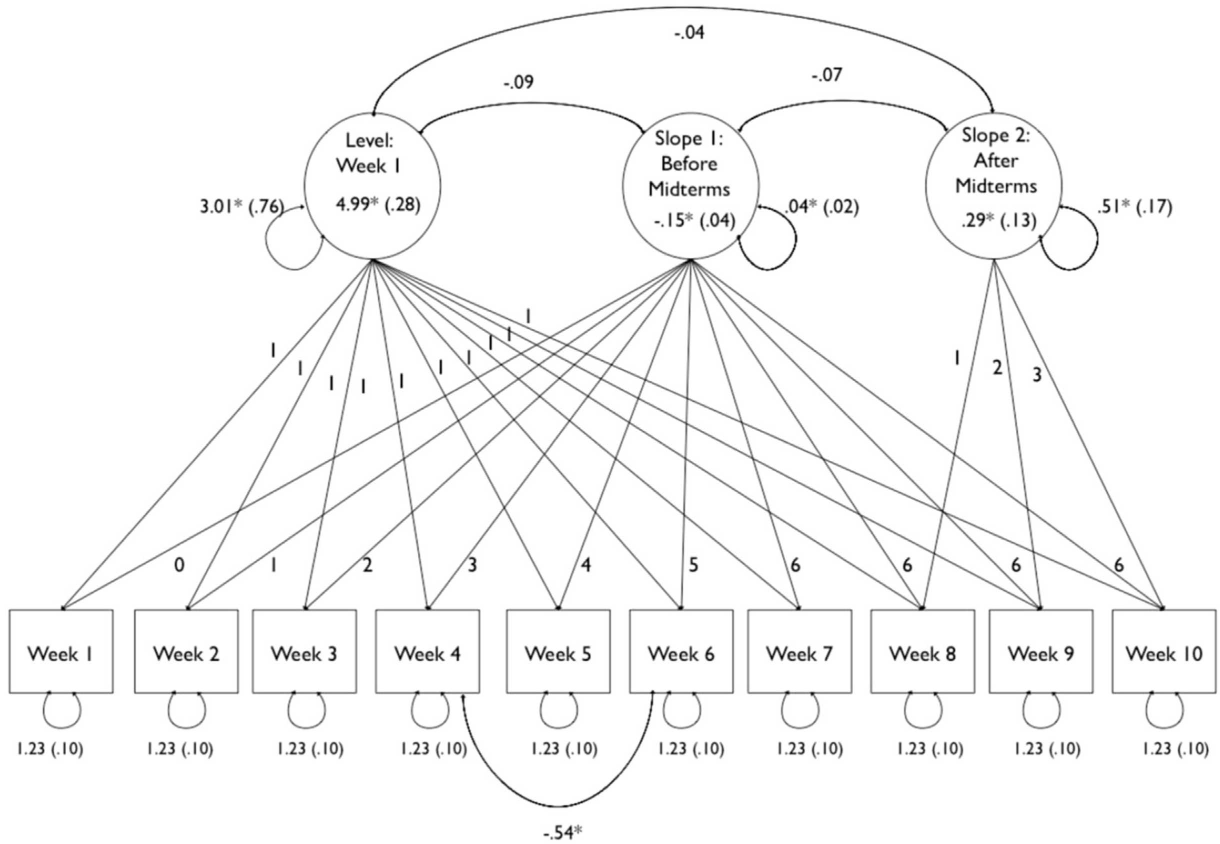

Fig. 3. Unconditional growth curve model for sociability during academic term. *p < .05

conditional models in which student ethnicity and academic class were entered as predictors of activity and sociability respectively.

3.3.1. *Ethnicity*

The coefficients for the conditional models predicting the activity and sociability behavior trajectories from ethnicity are shown in Table 2. Our results show that students' ethnicity was associated with the activity level at Week 1, such that Asian students tended to have lower activity durations during the first week of the term compared to Non-Asian students. In addition, students' ethnicity was associated with the sociability level at Week 1, such that Asian students tended to have lower sociability durations during the first week of the term compared to Non-Asian students.

3.3.2. *Academic class*

The coefficients for the conditional models predicting the activity and sociability behavior trajectories from academic class are shown in Table 2. Our results show that students' academic class was associated with the activity level at Week 1, such that upper classmen tended to have lower activity durations during the first week of the term compared to lower classmen. In terms of sociability, academic class was associated with the sociability level at Week 1, such that upper classmen tended to exhibit lower sociability durations during the first week of the term compared to lower classmen. Academic class was not associated with students' activity and sociability trajectories during the term.

4. Discussion

This study used a smartphone-sensing application to examine the patterns of stability and change that characterize a cohort of students' activity and sociability behaviors over the course of a 10-week academic term. Our findings contribute to the mHealth and applied psychology literature by demonstrating the viability of using smartphone sensing methods to track health-related behaviors in the context of students' daily lives. Moreover, the findings provide a fine-grained, descriptive account of how these behaviors may unfold during an academic term. Below we discuss our findings in regards to past research, and discuss potential application of the results for smartphone-based mHealth interventions in student populations.

Our results showed moderate to high rank-order stability estimates for activity and sociability durations across the academic term for this student cohort. These findings suggest that among these students, activity and sociability durations were highly stable behaviors from week-to-week. To our knowledge, no other study has used smartphone-sensor data to examine the rank-order stability of behaviors. The closest study to ours manually coded audio recordings of snippets of everyday life obtained from micro-recorders carried by participants for two 48-hour sessions separated by four weeks (Mehl & Pennebaker, 2003); those data yielded reliability estimates similar in magnitude to ours. Thus, the stability estimates obtained here, which are on par with the reliability estimates of self-reports, underscore the viability of using sensors to assess behaviors; these findings are particularly noteworthy given the high ecological validity and unobtrusiveness of the measures.

In terms of behavior change patterns, our results showed that for both activity and sociability, there were normative mean-level decreases during the first half of the term, before the midterm examination period. Our results indicate that as the term progressed, the students tended to engage in more sedentary behavior and affiliated with others less (i.e., spent less time proximal to ambient conversation), which may be related to the need to focus on studying and preparation for the exam period.

The pattern of large mean-level changes and high rank-order stability observed here points to the influence of situational factors in the college environment (e.g., exam periods, class deadlines, holidays) that generally operate in similar ways across participants to affect behavior. If the normative behavior-change patterns observed here replicate across campuses, smartphone-based mHealth interventions could be designed to deliver notifications to all students in the weeks preceding exam time, with suggestions to take breaks between study periods to move around and socialize with others. This type of intervention strategy could also help address previously observed associations between high frequency mobile phone use and greater sedentary behavior among college students (Barkley & Lepp, 2016).

Our results also showed that there was significant individual-level variability in the behavior-change patterns before and after the midterm period, indicating that not all the students conformed to the normative change patterns. The observed individual-level variation around the mean-level changes suggest that inter-individual differences may account for how students changed their activity and sociability levels in response to the shared stressor of the midterm exam period. For example, it is possible that some students chose to increase their physical activity or sociability as a response to the midterm exam weeks (e.g., running or socializing to relieve stress), while others may have decreased their physical activity or sociability (e.g., spending more time sedentary and alone to study).

We also examined whether socio-demographic characteristics (ethnicity and academic class), predicted individual differences in the cohort of students' activity and sociability trajectories. Our results showed that Asian and older students exhibited lower levels of activity and sociability at the start of the term, compared to Non-Asian and younger students. These findings support previous research that found a link between students' of ethnic minorities and upper classmen reporting less physical activity (e.g., Buckworth & Nigg, 2004; McArthur & Raedeke, 2009). The findings linking ethnicity with sociability were unexpected because this is the first study known to the authors that examines how patterns of change in sociability are associated with students' ethnicity. Further research is needed to determine whether the observed relationship between ethnicity and sociability is particular to the university setting of the current study, and whether it is observed among students from other ethnic minority groups. In addition, the findings linking academic class with sociability are a novel addition to the literature on health-related behaviors among students, suggesting that upperclassmen (e.g., seniors and graduate students) tend to spend less time affiliating with others than do lowerclassmen (e.g., freshmen and sophomores). This pattern might be due to differences in the situational contexts students experience as they progress through college. For example, many college students in the U.S. live in on-campus housing (e.g., dormitories, fraternity or sorority houses) during their first few years of college, and then move to off-campus housing as they get older (e.g., apartments, houses). It is possible that this change in students' living situation is partly responsible for the lower levels of sociability observed among older students. That is, students who live on campus would likely spend more time around ambient conversation, compared to those who live off campus.

4.1. Limitations

The current study has a number of limitations that need to be addressed in future research. The first concerns the characteristics of our student sample. The students were predominantly male, approximately half were of Asian ethnicity, and they were enrolled in a computer science course at a small Ivy League university. These students might have experienced different stressors and experiences during the academic term, compared to students at a larger university with potentially fewer academic demands, and compared to the broader population. A second limitation concerns the small sample size. As sensing apps become widespread tools for measuring health-related behavior, this preliminary work should be extended and replicated with larger samples of students from different institutions to determine whether the patterns observed generalize across samples.

A third limitation is that the sensors, while objective, may incorrectly infer certain micro behaviors. For example, when inferring sociability from the microphone sensor, it is possible that the audio classifier mistakenly underestimates the sociability of the participant by failing to capture conversation when the device is stored in the participant's bag, or overestimates the sociability of the participant by mistakenly inferring that the participant is engaged in conversation when they are watching TV alone. Moreover, the audio classifier picks up on ambient conversation but obviously does not capture other sociability behaviors and so may incorrectly infer that someone is not socializing when they are chatting with others via text messages or social media applications.

4.2. Future directions

The behavior trajectories observed in this study suggest that the students in our sample experienced potentially detrimental decreases in their activity and sociability levels prior to the midterm exams. The observed normative changes in these behaviors during the exam period raise the possibility that this period may be critical for the design of interventions targeting positive behavior change among students. To explore the generalizability of the substantive findings reported here, future studies should seek to distinguish whether the observed behavior-change patterns replicate in student samples from other universities and communities, or whether the patterns are unique to the campus life of the student population assessed in our study.

In addition, research is needed to explore the specific levels of activity and sociability that are associated with mental and physical health outcomes (e.g., stress, well-being, doctor visits), as well as their effects on other health behaviors (e.g., exercise, diet, sleep). In general, lack of physical activity has been associated with poor mental and physical health outcomes (American College Health Association, 2012; Maher et al., 2013; Warburton et al., 2006), and studies focused on loneliness, social isolation, or social support, suggest that low sociability negatively affects health and engagement in other health-related behaviors (e.g., lack of physical activity, irregular sleep hours; Allgöwer, Wardle, & Steptoe, 2001; Cohen, 2004; Shankar et al., 2011). However, the identification of critical thresholds for these behaviors (e.g., certain duration levels, frequency of physical activity or social interactions) could be instrumental in informing the development of mHealth interventions aimed at improving students' mental and physical health by setting thresholds for when attempts at changing their behavioral lifestyles should be made.

One interesting area of future research will employ sensing applications for the delivery of personalized mHealth interventions. For instance, personalized interventions could be designed that cater to how the student is responding to the stress of the term based on observed patterns in their sensor data (e.g., encouraging those with sedentary or social isolation patterns to improve them, and those with healthy activity and sociability patterns to maintain them). Moreover, the high stability estimates observed here could be useful to the health community because they suggest that activity and sociability behaviors are stable over time (as opposed to random). This information could be used to inform the design of mHealth interventions targeting these behaviors. For example, to promote enduring behavior change, smartphone-based notifications could be delivered to students several times a week, reminding them to be physically active and affiliate with others. Interventions that make the student aware of re-occurring unhealthy behavioral patterns (e.g., prolonged sedentariness or social isolation) may empower them to actively monitor their behaviors and enact positive change in their lifestyles (Wiederhold, 2015). Prototype smartphone-sensing applications have been developed that can deliver feedback that conveys information about a user's sensed activity and sociability levels (Eskes, Spruit, Brinkkemper, Vorstman, & Kas, 2016; Lane et al., 2011). The recent rapid growth in popularity of commercial activity tracking devices (e.g., Fitbit, Jawbone) suggests that such feedback could be effective in affecting behavioral change. However, more research is needed to test this type of intervention strategy and determine whether continuous feedback might lead to enduring behavior change.

We believe that the current findings provide a glimpse of what smartphone sensing methods are poised to offer for mHealth researchers interested in the connections between everyday behaviors and health outcomes. The current study examined durations of time students' spent active and affiliating with others (i.e., proximal to ambient conversation); however, future studies should also consider different aspects of activity and sociability behavior that can be captured using sensing applications because these data may reveal other critical periods of behavior change in activity and sociability patterns. For examples, accelerometer data can be used to classify duration of running or cycling behaviors specifically, or GPS data can be used to identify time spent at the gym or in social places (e.g., a fraternity or sorority house; Harari, Gosling, Wang, & Campbell, 2015). Similarly, microphone data can be used to classify active contributions to conversations, frequency of conversations, and other types of social interaction obtained from smartphone data logs (e.g., phone calls, text messages, social media app use; Harari et al., in press).

5. Conclusion

This study provides an important first step in illustrating the viability of using smartphone sensing applications for monitoring and obtaining detailed assessments of health-related behaviors. The study provides an initial descriptive portrait of how activity and sociability patterns may unfold for students as they go about their daily lives during an academic term. The findings showed that in a cohort of students, activity and sociability durations decreased during the first half of the term, and tended to increase again for sociability during the second half of the term. The students' sociodemographic characteristics also predicted individual variability in the behavior trajectories. We expect smartphone sensing methods will provide important insights into the objective behavioral patterns that predict consequential health outcomes, while pointing to target behaviors and periods of behavior change for the design of mHealth interventions.

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