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WITHDRAWAL BEHAVIORS AND MENTAL HEALTH AMONG COLLEGE STUDENTS

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Abstract

Youth social withdrawal has raised clinical concerns, and prevention of withdrawal behavior is important yet difficult. While human evaluation of withdrawal behavior can be subjective, technology provides objective measurement for withdrawal behavior. This study aims to examine the association between withdrawal behaviors (home-stay and non-communication) and mental health status (stress, depression and loneliness). The open-access StudentLife dataset, including the location and conversation information derived from the sensor data, stress levels, and pre- and post-questionnaires of depression (PHQ-9) and loneliness (RULS) of 47 college students over 10 weeks was used. Multilevel modeling and functional regression were employed for data analysis. Daily duration of home-stay was negatively associated with daily stress levels, and the interaction effect of daily duration of home-stay and non-communication were positively associated with daily stress levels and changes in PHQ-9 and RULS scores. Smartphone data is useful to provide adjunct information to the professional clinical judgement and early detection on withdrawal behavior.

KEY WORDS: *social withdrawal, mental health, college students, early intervention, behavioral assessment.*

Resumen

El aislamiento social de los jóvenes ha generado preocupaciones clínicas y prevenir estos comportamientos es importante pero difícil. Aunque la evaluación del aislamiento puede ser subjetiva, la tecnología proporciona medidas objetivas de este comportamiento. El objetivo de este estudio es examinar la asociación entre los comportamientos de aislamiento (permanecer en casa y no comunicarse) y el estado de la salud mental (estrés, depresión y soledad). Se utilizó la base de datos de libre acceso StudentLife, incluyendo información sobre la ubicación y la conversación registrada por un sensor de datos, los niveles de estrés y medidas de autoinforme pre y pos sobre depresión (PHQ-9) y soledad (RULS) de 47 estudiantes universitarios durante 10 semanas. Para el análisis de datos se utilizaron modelos multinivel y la regresión funcional. La duración diaria de la permanencia en casa estaba negativamente asociada con los niveles diarios de estrés y el efecto de interacción de la duración diaria de la permanencia en casa y la falta de comunicación estaban positivamente relacionados con los niveles diarios de estrés y los cambios en las puntuaciones en PHQ-9 y RULS. Los datos

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del teléfono inteligente son útiles para obtener información complementaria al juicio clínico profesional y para la detección temprana de los comportamientos de aislamiento.
PALABRAS CLAVE: *aislamiento social, salud mental, estudiantes universitarios, intervención temprana, evaluación conductual*.

Introduction

The ubiquitous of Information and Communication Technologies (ICT) in recent years has modified or even changed modern human, especially young people's behavior in developed countries. Apart from traditional youth risk behaviors (i.e., excessive alcohol use, illegal drug use, and heavy smoking), a new set of modern behaviors, including high use of Internet/TV/videogames for reasons not related to school or work, sedentary behavior and reduced sleep - altogether known as the "invisible" risk are associated with psychopathology and suicidal behaviors among young people across 11 European countries (Carli et al., 2014). In some developed countries, a similar emerging phenomenon with young people spending much time at home, engaging in isolated activities, and making minimal efforts to maintain face-to-face interpersonal relationships (Teo et al., 2015) was found to have negative impacts on young people at individual, familial, and societal levels (Li & Wong, 2015a). This new youth issue is identified in the United States, Spain, India, Oman, Japan, Korea, and Hong Kong, and named as youth social withdrawal behavior in the early 2000s (Li & Wong, 2015a, b). In Wong et al.'s (2015) study, they reported that young people aged 12-29 years who had been withdrawn for months had more negative life events and poorer mental health compared with the non-withdrawn ones.

Due to the withdrawn and invisible nature of youths with withdrawal behaviors, traditional research methodology that relies heavily on voluntary participation, self-reported questionnaires, and retrospective clinical assessment appear to be inadequate to fully examine such new youth behaviors in normal youth population. For example, clinical study examined youth patients who have to be 'staying at home almost all days' and for 'at least six months' (Kondo et al., 2013). However, some youths suffering from less severe but similar problems may go out on a regular basis, as if going to school, in order to hide their social withdrawal condition (Furlong, 2008). Along the same vein, some researchers suggested that some socially withdrawn youths do communicate with people unconnected to their lives, take trips with close friends, and maintain social contacts through digital means (Chan & Lo, 2014; Suwa & Suzuki, 2013). Those vulnerable youths may not be classified clinically as problematic because they do not stay at home almost all days and avoid all interpersonal relationships. Helping professionals such as social workers, however, suggest that those vulnerable youths should also be intervened for preventing more severe withdrawal (Li & Wong, 2015b). It seems that in order to fully examine this new set of youth withdrawal behaviors, novel research methodology is needed to provide a less arbitrary understanding and definition for such problematic behaviors.

Advanced mobile technologies that have become ubiquitous in recent years in many societies may help to expand our understanding of young people's invisible risk behaviors. For instance, interactions of human behaviors, locations, and the environment can be captured non-intrusively by multi-modal sensors in mobile phones such as accelerometers, global positioning systems (GPS), and light sensors (Ben-Zeev, Scherer, Wang, Xie, & Campbell, 2015) and form a big data set that could be more representative and less subjective. Indeed, a systematic review shows that previous studies employed mobile technologies to assess people's locations of physical activity and sedentary behavior (Loveday, Sherar, Sanders, Sanderson, & Esliger, 2015).

This exploratory study attempted to examine whether individuals' home-stay and non-communication can be objectively measured using smartphone sensors; and whether such withdrawal behaviors are related to their psychological status in a longitudinal manner. If, as found in previous studies, withdrawal behaviors are related to mood or stress-related disorders (Koyama et al., 2010), and heightened levels of loneliness (Teo et al., 2015), this leads to the hypothesis that duration of home-stay and non-communication can be taken as measures of severity of negative impacts of withdrawal behaviors, and are positively associated with individuals' stress, depressive and loneliness levels in an increasing trend over time. The findings of this study may shed light on the understanding of the definition of youth social withdrawal.

Methods

The StudentLife dataset

The StudentLife dataset was collected by researchers in the United States and made open-access over the Internet (Wang et al., 2014). The purpose of the StudentLife study was to use less-intrusive and automatic sensor data from smartphones of students to assess their mental health, academic performance, and behavioral trends. All students enrolling in a computer science programing class at Dartmouth College were invited to participate in the study and 47 of them (64% undergraduate students and 36% graduate students) participated in the study. The response rate was 63% and the dropout rate was 22%. These participants were 79% male, 49% Asian, 47% White, and 4% Black/African American and their average age was 22.5 years (range: 19 -30).

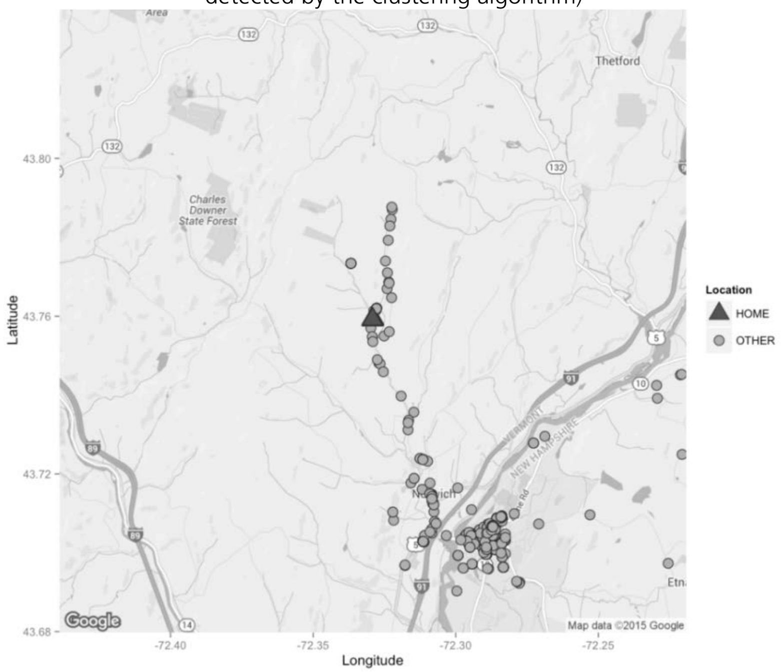
In the study, sensor data were collected over a 10-week period in the spring of 2013 using smartphones with several embedded sensors including microphone, GPS, wireless fidelity (WiFi) receiver, accelerometers, and light sensor. Sensor data were collected continuously and did not require student activation. Nevertheless, students needed to respond to scheduled ecological momentary assessments (EMA) to obtain data such as stress levels through their smartphones over the 10-week period (Shiffman, Stone, & Hufford, 2008). Students also completed online questionnaires a day prior to study commencement, as well as a day after the study. The pre- and post-questionnaires provided information on students' changes in depression and loneliness. Details of data collection, privacy considerations and data quality were reported elsewhere (Ben-Zeev et al., 2015; Wang et al., 2014). This study made use of the open-access StudentLife dataset including the location and conversation information derived from the sensor data, stress EMAs, and pre- and post-questionnaires about depression and loneliness.

Feature extraction from sensor data

Daily duration of home-stay. The StudentLife dataset has two types of location information: GPS and WiFi location. The smartphone sensors collected participants' locations between every 10-20 minutes. Based on the location data and corresponding time, the cluster most visited during the time period between 12 a.m. and 6 a.m. was identified as the home cluster (Saeb et al., 2015). The number of location clusters was found by the k-mean algorithm, using the Euclidean distance matrix. The home location was derived from the cluster head, which was calculated by the mean latitude and longitude. Figure 1 shows a participant's location data and his identified home location as an example (Kahle & Wickham, 2013). Daily duration of home-stay was measured by the number of hours a participant spent at home on a daily basis. It is defined as the duration in which the distance between home location and the location reported is less than 50 meters.

Figure 1

Example GPS location data, overlaid on Google map (The triangle show the home cluster detected by the clustering algorithm)



Daily duration of non-communication. The StudentLife dataset has the conversation information: the time and duration of participants' conversations. StudentLife researchers collected microphone data and implemented classifiers on the smartphones to infer human voice and detect conversation. This approach was shown to have 85.3% accuracy in detecting conversations (Lane et al., 2011). Daily duration of non-communication was calculated as 24 hours minus the number of hours of a participant's conversations daily.

Instruments

a) Daily stress level. Prompts to complete self-report stress ratings appeared daily on the smartphone at randomly selected time points during the day (average weekly response rate: 4.9 days a week; Ben-Zeev et al., 2015). The single-item measure was "Right now, I am . . ." with 5-point Likert scale (1= Feeling great to 5= Stressed out). Daily stress levels were calculated as the stress ratings for each individual every day.
b) *The Patient Health Questionnaire-9* (PHQ-9; Kroenke, Spitzer, & Williams, 2001; Spitzer, Kroenke, & Williams, 1999) is a nine-item self-rated measure of depressed symptomology based on the Diagnostic and statistical manual diagnostic criteria for major depressive disorder. Each item is rated on a 4-point Likert scale (0= not at all to 3= nearly every day). The score range is 0 to 27, with higher scores indicating greater symptom severity of depression. Scores were shown to be significantly associated with depression (r= .73; Kroenke et al., 2001). The PHQ-9 has high internal consistency from several studies (α= .86-.89) and test-retest reliability (r= .84). The original validation report on the PHQ-9 indicated adequate psychometric properties (Kroenke et al., 2001). The PHQ-9 was used to examine hikikomori in the United States (Teo, 2013). In the StudentLife study, 38 participants completed both the pre- and post- PHQ-9.
c) *The Revised UCLA Loneliness Scale* (RULS; Russell, Peplau, & Cutrona, 1980; Russell, 1996) is a 20-item self-rated questionnaire that assesses one's feelings of loneliness and social isolation. Each item is rated on a 4-point Likert scale (1= never to 4= always). The score range is 20 to 80, with higher scores indicating greater subjective feelings of loneliness (Russell, 1996). Scores were shown to be significantly associated with the amount of time individuals are alone each day (r= .41), and the number of close friends they have (r= -.44; Russell et al., 1980). The RULS has high internal consistency reported from several studies (α= .94), and extensive evidence of construct, concurrent, and discriminant validity was reported by Russell and colleagues (1980). The RULS was used to examine hikikomori in four countries including India, Japan, Korea and the United States (Teo et al., 2015). In the StudentLife study, 37 participants completed both the pre- and post- RULS.

Statistical analyses

There were two analyses in the study including multilevel modeling for repeated measures and functional regression. First, we conducted multilevel modeling for repeated measures to examine the associations between daily stress levels (outcome) and daily durations of home-stay and non-communication (covariates) from time 0 (the first week of the study) to time t (the last week; Bates, Mächler, Bolker, & Walker, 2015). Daily durations of home-stay and non-communication of each participant were averaged weekly for multilevel modeling and functional regression. We employed group-mean centering such that the daily durations were centered on the individual means. In the model, both between-subjects (covariate) and within-subject (time) effects were evaluated. Second, we conducted functional regression to examine the associations between daily duration of home-stay and non-communication in the 10 weeks (functional predictors) and pre- and post-changes in PHQ-9 and RULS scores (outcomes; Febrero-Bande & Oviedo de la Fuente, 2012). A smooth nonparametric function was fitted to each individual's predictor variable using principle component basis splines. A set of functional regression coefficients was fitted to the functional predictor variables to predict the three outcomes. An *F* statistic was calculated for each functional regression model and the p value was the significance of the association between the outcome and the functional predictor.

Results

The descriptive statistics of daily durations of non-communication and home-stay and stress levels in the 10 weeks are shown in Table 1. The multilevel model is shown in Table 2. In the model, there is a significant main effect of daily durations of home-stay on daily stress level (estimate= -.04, *SE*= .02, *p*= .0271). There is a significant interaction effect of daily durations of home-stay and non-communication on daily stress level (estimate= .03, *SE*= .01, *p*= .0228). The positive relationship between daily duration of home-stay/ non-communication and daily stress level was stronger provided that daily duration of home-stay/ non-communication is long. About 36% (intra-class correlation= .36) of the variation in daily stress level over time was attributed by the inter-individual differences whereas about 64% of the variation was intra-individual differences. The estimated correlation between the intercepts and slopes was negative and large (*r*= -.41). Participants with higher daily stress levels in the beginning were associated with less positive growth on daily stress levels over time.

Significant pre- and post-changes were seen in PHQ-9 and RULS (*p*< .001 and *p*= .02, respectively) when evaluated with a Wilcoxon signed-ranks test. In the functional regression analysis, daily duration of non-communication was significantly associated with changes in PHQ-9 and RULS scores (both *p*< .001). The significant associations are illustrated in Figure 2 with the functional regression coefficient plotted along with 95% confidence intervals. The regression coefficients indicate that earlier in the study (Weeks 1-5), increased daily duration of non-communication was associated with negative PHQ-9 and RULS change scores; whereas in the later weeks (weeks > 5), the direction of the association changed such that increased duration was associated with positive PHQ-9 and RULS change scores. There were no significant associations between daily duration of home-stay and changes in PHQ-9 (p= .3443) and RULS scores (p= .4273). Daily durations of non-communication and home-stay was significantly associated with changes in PHQ-9 (p= .0226) and RULS scores (p= .0277). During the later weeks of the study (weeks > 6), increased daily duration of non-communication and home-stay was associated with positive PHQ-9 and RULS change scores.

Table 1

Descriptive statistics of daily duration of non-communication and home-stay and stress levels in the 10 weeks

	Daily duration of non-communication (hours)		Daily duration of home-stay (hours)		Stress (1 to 5 rating)	
	M	*SD*	*M*	*SD*	*M*	*SD*
Week 1	18.4846	1.9703	13.3914	5.1425	2.5275	0.9325
Week 2	18.1311	2.2441	13.4162	3.7277	2.4269	0.9377
Week 3	18.7628	2.1896	13.5957	5.0702	2.2361	0.9312
Week 4	18.7866	2.1822	13.3801	4.7399	2.1006	0.8055
Week 5	18.906	2.4282	13.9191	4.1403	2.1475	1.0884
Week 6	19.7316	1.8667	13.3868	5.1226	2.1686	0.7124
Week 7	19.2246	2.1881	15.1344	4.1512	1.9399	0.9263
Week 8	20.0046	1.6987	15.0905	4.4661	2.1841	1.2199
Week 9	18.9268	1.8269	13.0252	4.9175	2.2453	0.9225
Week 10	16.7933	1.6365	12.2773	4.0557	2.1666	1.2583
Overall	18.8595	2.1455	13.7259	4.5589	2.2334	0.9361

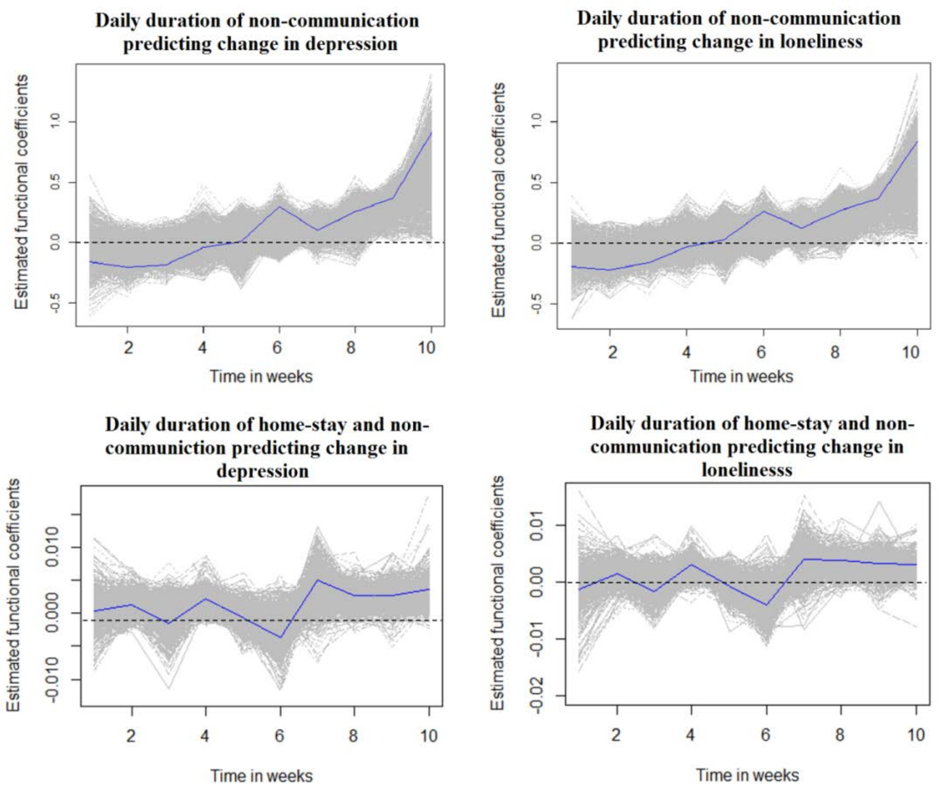
Table 2

Multilevel modeling for the relationship between daily duration of home-stay and non-communication, and daily stress level

Covariate	Estimate	Standard error	*p* value
Fixed effects			
Intercept	2.4040	0.1258	
Time	-0.0407	0.0234	0.0812
Daily duration of non-communication in a week	-0.0135	0.0415	0.5093
Daily duration of home-stay in a week	-0.0429	0.0179	0.0271
Daily duration of non-communication * Daily duration of home-stay in a week	0.0315	0.0139	0.0228
Random effects	Variance	*SD*	Correlation
Intercept	0.3137	0.5601	
Time	0.0021	0.0458	-0.41
Residual	0.5541	0.7444	
Model fit statistics			
-2logL= -326.8, AIC= 671.6 & BIC= 704.0			

Figure 2

Estimated functional coefficients and 95% confidence intervals from functional regression models (The solid line is the estimates and the gray area is the confidence intervals)



Discussion

This exploratory study made use of an open-access dataset collected through EMA and self-reported questionnaires to investigate whether one's non-communication and isolated behaviors could be identified as associated behaviors with one's mental health among college students. It is interesting to find that in this ICT era, home-stay does not associate with a poor mental health status; instead only long duration of home-stay and non-communication through physical means with others are associated with higher stress, depressive, and loneliness levels. In applications of this finding into the study of social withdrawal, the finding supports that both prolonged home-stay and non-communication are the essential factors associated with the negative impacts of withdrawal behaviors. Non-communication alone was not associated with poor mental health status initially in the first five weeks, and it was only found later associated with poor mental health status starting from the sixth week. This association was also observed in previous studies, in which some youths staying at home but occasionally going out suffered from similar problems with socially withdrawn youths (Furlong, 2008). The longitudinal data allows us to understand that target-oriented and voluntary physical isolation and non-communication with others do not have adverse effects initially; however, after weeks of social isolation, the impacts become negative when the condition is prolonged to about six weeks. All in all, it seems that the data collected through EMA can also be useful to provide adjunct information to the professional clinical judgement and self-reported data to examine youth social withdrawal behavior.

There are some limitations in this study. First, the sample size in the study is small and not representative so the results may not be generalizable to a larger population and other cultures. Further study will recruit a larger sample size in different settings not limited to college. However, this study provides insight on using smartphone sensing for understanding withdrawal from the behavioral science perspective. Second, the participants' demographic information such as age and gender are not provided in the StudentLife dataset and the influence of demographics such as gender difference was not examined in the analyses. The psychiatric conditions are also not provided in the dataset. As youth social withdrawal is classified based on whether it is caused by psychiatric disorders (secondary withdrawal) or not (primary withdrawal; Li & Wong, 2015b), without knowing the participants' psychiatric conditions, it is uncertain whether the withdrawal behaviors are primary or secondary, and appropriate interventions cannot be recommended. Third, limited research investigated the accuracy of extracting behaviorally meaningful features such as duration of home-stay and conversation from smartphone data. For instance, the smartphone speech-detection system may not accurately differentiate live human speech (conversation) from radio or TV generated audio (Ben-Zeev et al., 2015). Fourth, other forms of non-verbal communication such as text messaging were not investigated due to the constraints of the dataset. The focus was merely on verbal/spoken communication, whereas much of young people's communication in modern societies takes place using digital means - texting, social media use etc. The absence of verbal conversation thus does not necessarily constitute the absence of communication, nor does it necessarily indicate a withdrawal from 'social life'.

Regardless of these limitations, this exploratory study provides practical implications on early detection and potentially preliminary diagnosis for youth social withdrawal in the future. While the concept of youth social withdrawal is complicated and fuzzy, withdrawal behaviors can be measured objectively by mobile sensors and investigated for the tendency to be complete social withdrawal. Since most socially withdrawn youths tend to be avoidant, it is difficult to engage and intervene them during their social withdrawal period. Early detection of socially withdrawn youths is important for effective mental health and youth services. Furthermore, the novel mobile health research methodology of extracting behaviorally meaningful features from sensor data and analyzing subtle behavioral changes also provides significant research implications on investigating other contemporary mental health issues. For example, the technique may be applicable to investigating mental issues such as social anxiety and social phobia (Caballo, Salazar, Irurtia, Arias, & Nobre, 2013; Garcia-Lopez, Diez-Bedmar, &

Almansa-Moreno, 2013; Olivares, García-López, & Hidalgo, 2001). Mobile sensing can provide more evidence and insights on subtle behavioral changes which is regarded as problematic but difficult to be identified by human observation (Carli et al., 2014). For example, other "invisible" risk behaviors such as reduced sleep, increased sedentary behaviors, media use and solitary behaviors can be investigated in future research.

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