HHS Public Access

Author manuscript

Inf Commun Soc. Author manuscript; available in PMC 2019 January 01.

Published in final edited form as:

Inf Commun Soc. 2018 ; 21(2): 163–173. doi:10.1080/1369118X.2016.1266374.

The Relationship Between Social Media Use and Sleep Quality among Undergraduate Students

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Abstract

Insufficient sleep is a growing health problem among University students, especially for freshmen during their first quarter/semester of college. Little research has studied how social media technologies impact sleep quality among college students. This study aims to determine the relationship between social media use and sleep quality among freshman undergraduates during their first quarter in college. Specifically, we explored whether variations in Twitter use across the time of day and day of the week would be associated with self-reported sleep quality. We conducted a study of Freshman Twitter-using students (N = 197) over their first quarter of college, between October to December of 2015. We collected students' tweets, labeled the content of the tweets according to different emotional states, and gave theme weekly surveys on sleep quality. Tweeting more frequently on weekday late nights was associated with lower sleep quality ($\beta = -0.937$, SE = 0.352); tweeting more frequently on weekday evenings was associated with better quality sleep ($\beta = 0.189$, SE = 0.097). Tweets during the weekday that were labeled related to the emotion of fear were associated with lower sleep quality ($\beta = -0.302$, SE = 0.131). Results suggest that social media use is associated with sleep quality among students. Results provide can be used to inform future interventions to improve sleep quality among college students.

Keywords

Sleep Quality; University Students; Social Media; Twitter; Emotions/Mood

Introduction

Insufficient sleep is an increasingly important health problem in the United States. According to the Centers for Disease Control and Prevention (CDC), greater than 30% of adult Americans get an insufficient quantity of sleep, defined as less than seven hours of

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Disclosure Statement: There is no financial interest or benefit for any author and there is no conflict of interest to report. Additionally, there is no funding to report for this study.

sleep per night (Center for Disease Control (CDC), 2013). Americans recognize this problem, with greater than 35% of adults reporting their quality of sleep as “poor” or “only fair” (National Sleep Foundation, 2014). To address the growing sleep epidemic, research is needed on more recent factors that might affect sleep deprivation, such as the relationship between sleep and new technologies like social media.

At the root of the poor sleep epidemic are chronic issues rather than occasional aberrant nights of acute sleep deprivation (Center for Disease Control (CDC), 2013). The consequences of chronic sleep problems can be severe (Banks & Dinges, 2007). Insufficient sleep causes a variety of health problems, including an increased likelihood for accidents (Committee on Sleep Medicine and Research & Board on Health Sciences Policy, 2006), increased rates of obesity/diabetes (Knutson, Spiegel, Penev, & Cauter, 2007), increased age-related chronic problems (Spiegel, Leproult, & Van Cauter, 1999), and decreased cognitive capacity (Harrison & Horne, 2000).

University students, especially freshmen students, are especially impacted by the sleep epidemic (Jensen, 2003). In one study, more than 76% of university students reported occasional sleep problems (Vail-Smith, Felts, & Becker, 2009), and in a series of studies 12% to 42% of students reported regular poor sleep quality (Buboltz Jr, Brown, & Soper, 2001; Carney, Edinger, Meyer, Lindman, & Istre, 2006; Vail-Smith et al., 2009). Freshmen students, in addition to learning how to cope with academic stress, must also adapt to a new environment while transitioning into young adulthood (Richter, 2015; Terenzini et al., 1994). Outside of this, over the past decade there has been a large increase in the share of young adults using social media (Perrin, 2015), and previous studies have shown that greater social media use is associated with lower stress levels (Hampton, Rainie, Lu, Shin, & Purcell, 2015).

Measuring how young adults communicate their sleep habits on social media, and inversely how their social media habits are related to the quality of their sleep, is a growing field of research. Studies over the past decade have linked electronic media use by young adults with reduced total sleep time and sleep quality (Cain & Gradisar, 2010). More recently, studies have linked higher rates of social media use to greater sleep disturbance (Levenson, Shensa, Sidani, Colditz, & Primack, 2016) and obsessive Facebook checking (i.e., a task requiring less cognitive effort) to lower quality sleep (Mark, Wang, Niiya, & Reich, 2016). Higher daily use of texting among freshmen has also been linked to greater sleep problems (Murdock, 2013). Additionally, research focusing on Twitter use among the general population has shown that tweet sentiment varies throughout out the day as a consequence of people’s sleep and circadian rhythm (Golder & Macy, 2011). Specifically, positive affectivity on Twitter is higher on weekdays and that it peaks as people wake up before gradually decreasing throughout the day (Golder & Macy, 2011).

In this study, we sought to determine the relationship between quality of sleep for freshmen students and their patterns of social media use during their first quarter in college. Specifically, the study explored how variations in Twitter activity across the time of day and day of the week were associated with self-reported quality of sleep.

Methods

Freshmen students at the beginning of academic year 2015 were recruited (in-person and through Facebook advertisements) from the University of California, Los Angeles (UCLA). Recruitment began on September 14th and ended on October 23rd (the fourth week of class). To qualify for the study, students had to be active Twitter users, tweeting at least three times a week.

Participants completed a short online survey each week that measured students' stress levels, methods of dealing with stress, and emotional levels. Subjects were provided $5 (U.S.) for each completed survey and an additional $5 if all surveys were completed in a month (total possible compensation: $75). This money was disbursed as Amazon gift cards post-study.

The UCLA Institutional Review Board approved the study protocol. Prior to obtaining in-person consent, participants were provided with oral/written descriptions of the protocol. Additional inclusion criteria stated that students must be: a freshman/first-year transfer, in their first quarter, and younger than 21.

Measures

Demographics—The first survey included a questionnaire on gender, race/ethnicity, age, sexual orientation, state/country of birth, parental information (marital status and highest education attained), social networking site use, academic major, and SAT score.

Weekly Survey—Each week students reflected on their previous week and provided self-assessments of multiple wellness measures including: quality of sleep, stressors experienced, methods of dealing with stress, and emotional health. Each element was rated using a five-point Likert scale.

Tweets/Retweets—Twitter is a social media site where users can write tweets of 140 characters or less and/or forward tweets written by someone else (called *retweets*). All tweets (n= 21,491) and retweets (n = 14,454) for all participants were downloaded during the three-month study using Twitter's Rest API. If a user's account was private, study staff contacted the participant to request that they momentarily allow access to the account.

The tweets were cleaned to remove English stop words (e.g. "the", "and" "that"). All tweets were categorized into five emotion categories: fear, anger, love, joy, or neutral using machine learning model (a Naïve Bayes classifier). In order to train our machine learning model, a sample of 3,500 tweets was randomly selected to be hand-coded by two study staff into one of five emotion categories. Retweets were not considered, as these were not written by the subjects and studies have shown that they do not reflect an individual's emotions (Chew & Eysenbach, 2010). After hand-coding, joy (22.1%) and fear (17%) were the most common emotions expressed (not considering neutral [25.8%]). The 3,500 hand-coded tweets were placed into a machine learning model (a Naïve Bayes classifier) to predict the emotions in the remaining tweets. The classifier used a bag-of words approach. Monograms that appeared in at least three tweets, bigrams that appeared in at least six tweets, trigrams that appeared in at least three tweets were included. Additional features included the time, day of

week, and the week when the tweet was sent, plus the length of the tweet. Separate models were run for each emotion, allowing for tweets to be classified as having several emotions at once.

Leave-one-out cross-validation (with a 80/20% train/test split) was used to assess model accuracy. The estimated accuracy of each model was relatively high, with the model predicting anger in tweets having the highest accuracy (89.4%). The accuracy for the other emotions was as follows: love (83.4%), fear (79.4%), joy (74.5%), and neutral (69.5%). The trained models were then used to classify the remaining tweets that were not hand coded. All natural language processing and prediction analysis was done using NLTK and scikit-learn in IPython.

Data Analysis

This longitudinal study spanned 10 weeks of the first quarter of freshmen year. The objective was to estimate the relationship between the quality of sleep and Twitter use for freshmen students. All regressions used the self-reported quality of sleep as the dependent variable in a linear mixed effects model. Analyses were conducted with RStudio version 0.99.489 (RStudio, Boston, MA, USA) using the nlme package and restricted maximum likelihood estimation (REML). Random effects were specified for the participants (i.e., intercept random effects) and time periods (i.e., slope random effects). Additionally, splines (using the lmeSplines package) were included for the time periods to account for the non-linear nature of the data. A linear mixed effects model allowed for analysis of the high correlation between repeated measures (D. M. Bates, 2010; D. Bates, Mächler, Bolker, & Walker, 2014). A likelihood ratio test (LRT) against a null model determined statistical significance. Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were also used to determine the fitness of the model.

The full model used in this paper is listed below. All predictor variables were included in separate regressions:

$$\begin{aligned}&\text{Quality of Sleep}_t \sim 1 + \text{Week} + \text{Female} + \text{Ethnicity} + \text{Academic Major}\\&+ \text{Log(Tweets/Week)}_t + \text{Predictor Variable}_t + (1 \mid \text{Week}) + (1 \mid \text{Student})\end{aligned}$$

Results

Demographics

265 students took the online screening survey. 212 students consented to participate in the study. By the time of the first data collection, 197 students remained in the study (12 students dropped out and 3 students were disqualified for not being freshmen). The 10 weeks of data collection began on the third week of classes and lasted until winter break in early December.

181 students (92%) responded to the baseline demographics survey. There were a total of 1,550 observations during the 10 weeks of the study, for a weekly average response rate of

84%. Tests for differences at the baseline between the students who dropped out and students who remained in the study showed no significant differences.

The average age was 18 and 60.2% were female (Table 1). More than 85% of the students had declared a major by the time of enrollment, with the largest share of students in the study (42.5%) consisting of health science/biology students.

The sample closely matched the general population of UCLA freshmen, which is an average age of 18.5 years old and 56% female. However, our sample contained a noticeably higher representation of Hispanic and Black students (sample = 29.3% and 11.6%, respectively; UCLA = 22.9% and 4.9%, respectively) and possibly multiracial students (sample = 6.1% and an unreported value by the UCLA registrar). Additionally, there was a higher representation of students majoring in health science/biology versus the general undergraduate population (sample = 42.5%; UCLA = 29.3%) (“Enrollment demographics, Fall 2015,” 2015, “Undergraduate Profile (Undergraduate Profile),” 2014).

Twitter usage and emotions expressed

Tweets were successfully downloaded from 166 of the 181 students who finished the baseline survey. Of the missing students, three students did not tweet during the three-month study, six students had private accounts and were unresponsive to inquiries from research staff, five accounts had been deleted, and one account had been suspended by Twitter. Table 2 contains a summary of the 21,491 tweets and 14,454 retweets (35,946 total tweets). This resulted in a weekly average of 3,595 total tweets and a per-subject average of 217 total tweets. The frequency of the predicted emotions is shown in Table 2, with joy (18.7%) and fear (12.4%) being the most commonly classified emotions.

Figure 1 highlights the variation across a 24-hour period. The daily pattern can be expressed as follows: there was a steady increase between 6 A.M and Noon/1 P.M., after this was general stability until 7 P.M. another increase occurred that plateaued between 9 P.M and Midnight, and finally a lull was reached between 2 A.M and 6 A.M. To capture this, the 24-hour day was broken into four periods. Period 1 (morning/lunch) captures 6:00 A.M. to 1:00 P.M., period 2 (afternoon) captures 1:00 P.M. to 7:00 P.M., period 3 (evening) captures 7:00 P.M. to 2:00 A.M., and period 4 (late night) captures 2:00 A.M. to 6:00 A.M. Table 2 contains the summary data.

Tweets were also categorized according to length, as measured by the number of individual elements in a tweet. An element could be a word, an acronym/abbreviation, a number, an emoticon, a text emoticon, a link, or a hashtag. All elements beginning with “@” were eliminated, as this designates a recipient of a tweet. The average length of a tweet was 9 elements, with a minimum of 0 and maximum of 45. Tweets were then categorized according to the quartile distribution of the length (Table 2).

Quality of Sleep

The average value of self-reported quality of sleep was 3.08 (SD = 0.88). This indicates that students reported an average quality of sleep across the study. However, the average weekly value varied throughout the semester (Fig. 1). The weeks with the lowest reported sleep

quality were during midterms (mean = 2.96; SD = 0.83) and final examinations (mean = 2.90, SD = 0.95), while the week with the highest occurred one week prior to finals (mean = 3.41, SD = 0.94).

After merging the weekly survey dataset with the Twitter dataset of 166 students, the mean reported sleep level was 3.07 (SD = 0.88), with no significant difference between the 166 remaining students and 15 missing students.

Weekly Sleep Quality and Twitter usage

The relationship between sleep quality and twitter usage are shown in Table 3. Tweeting more during late night on weekdays resulted in poor sleep quality ($\beta = -0.937$, SE = 0.35), meanwhile tweeting more during evenings was associated with better quality sleep ($\beta = 0.19$, SE = 0.09). However, we did not observe this difference on the weekends.

Students that tweeted shorter tweets on weekdays late at night were associated with poor sleep quality ($\beta = -0.41$, SE = 0.14) and longer tweets ($\beta = 0.20$, SE = 0.09) were associated with better sleep quality. A greater proportion of tweets characterized by fear during weekdays was associated with lower sleep quality ($\beta = -0.30$, SE = 0.13). There were no other significant association for the length of a tweet, emotion of the tweets on sleep quality on the weekends.

Discussion

This three-month study explored the relationship between the self-reported quality of sleep and social media activities of freshmen college students during their first academic semester. This is one of only a few studies that have tracked freshmen sleep patterns (Galambos, Howard, & Maggs, 2011; Miller, Shattuck, & Matsangas, 2010), and the only one we know to longitudinally combine a sleep study with extensive social media data.

The first major finding indicated a link between sleep quality and when students used social media during the course of a week. Students who tweeted more frequently on weekday late nights (2:00 A.M.–6:00 A.M.) reported a significantly lower quality of sleep, yet if they tweeted more frequently on weekend late nights there was no significant relationship. Interesting tweeting more during weekday evening was associated with better sleep. From these findings, it might also be argued that engagement with Twitter is reflective of student schedules (i.e., during weekdays, many students have classes in the morning and tweeting late at night indicates that they are not sleeping. The finding for a difference between weekdays and weekends is consistent with the findings reported in Golder and Macy (2011) (Golder & Macy, 2011).

A secondary analysis showed that freshmen sleep quality was not just related to the temporal aspects of tweeting, but also to the content of the tweets. For late night tweets, when students wrote a greater share of “short” length tweets, they reported lower quality of sleep. Akin to this finding is that when freshmen wrote a greater share of “long” tweets on weekday evenings, they reported a higher quality of sleep. Importantly, there were no other significant relationships found between tweet length and the time of day on weekdays. A

similar finding was reported in a study by Mark et al. (Mark et al., 2016), which showed that repetitive Facebook status checking late at night is linked with lower quality of sleep in students. The argument in this study is that writing a short tweet requires less effort than writing a long tweet, and that more frequent late night short tweeting could be a Twitter-equivalent to repetitive late-night Facebook checking. Remarkably, more frequent longer tweets in the evening were associated with better quality sleep, indicating that better sleepers engage Twitter differently than poorer sleepers. One possible explanation for this finding is that better student sleepers participate in more social and conversational tweeting at night, while another is that better sleepers have positive habits that reinforce their sleeping schedule.

Finally, this paper established that levels of fear expressed by freshmen in their social media activities were related to sleep quality. The tweets written by the students reflect their emotional state, and fear is an especially important emotion for freshmen given the high levels of academic stress and other life changes during freshmen year. This finding confirms a link between student sleep quality and mood/emotions (Galambos, Dalton, & Maggs, 2009) and underscores the primacy of fear as compared to other emotions for freshmen.

There are several limitations to this study. First, the sample was restricted to active Twitter users (> 3 posts/wk), which may have led to an overrepresentation of minority students. Twitter is popular among Black/Latino youths, with 40% of black versus 29% of white 18- to 29-year-olds using Twitter (Gesenhues, 2014). We believe this is a positive aspect in our study, as minority students are high-risk for a number of public health issues. In addition, having an overrepresented sample of minority students can help to better understand poor sleep among these groups. Second, the sample included a high number of health science major students. Fitness trackers were distributed to participants, which could explain why a larger share of health science students participated in the study. Third, this study only tracked the first quarter, rather than the entire year. A longer study could provide for extended conclusions about how freshmen students adjust to academic life.

Conclusion

This study tracked the self-reported quality of sleep and social media habits of 197 freshmen over their first quarter at a major university. It was shown that weekday tweeting late at night (2:00 A.M.–6:00 A.M.), especially posting shorter tweets, was associated with poorer quality sleep. It was also shown that tweeting during evenings (7:00 P.M.–2:00 A.M.), especially posting longer tweets, was associated with better quality sleep. Finally, as freshmen posted more fear-related tweets, their reported quality of sleep decreased. This study established Twitter as an important source of data for predicting freshmen sleep quality, and thus their overall well-being during a particularly stressful time of life.

Biographies

Renee Garett – Renee Garett is a licensed clinical social worker and the Founding Director of ElevateU, an organization that conducts research and development on technologies to address at-risk populations, particularly youth.

Dr. Sam Liu – Dr. Sam Liu received his PhD from University of Toronto in public health and health promotion. His research focuses studying the effects of digital communication technology on health behaviors.

Dr. Sean Young – Dr. Sean Young received his PhD in Psychology and MS in Health Services Research from Stanford University. Dr. Young is the Executive Director of the University of California Institute for Prediction Technology and an Associate Professor in the Department of Family Medicine at the University of California, Los Angeles.

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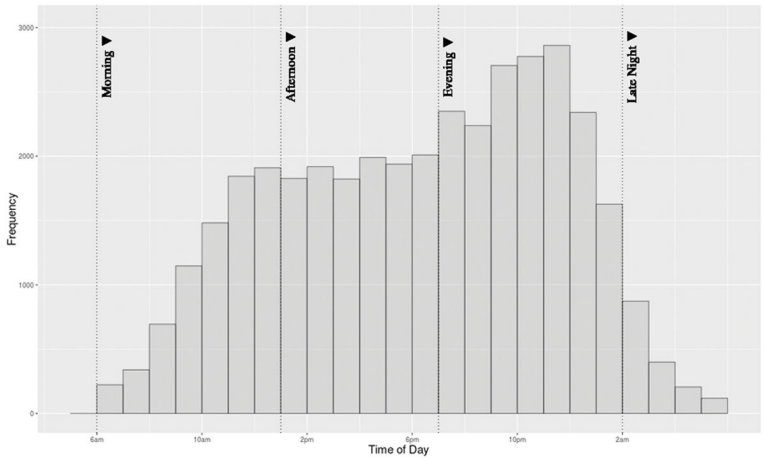

Figure 1.

Histogram of Tweets/Retweets by Hour for Freshmen Students at the University of California, Los Angeles During the Fall Semester 2015 (n = 181), Los Angeles, CA

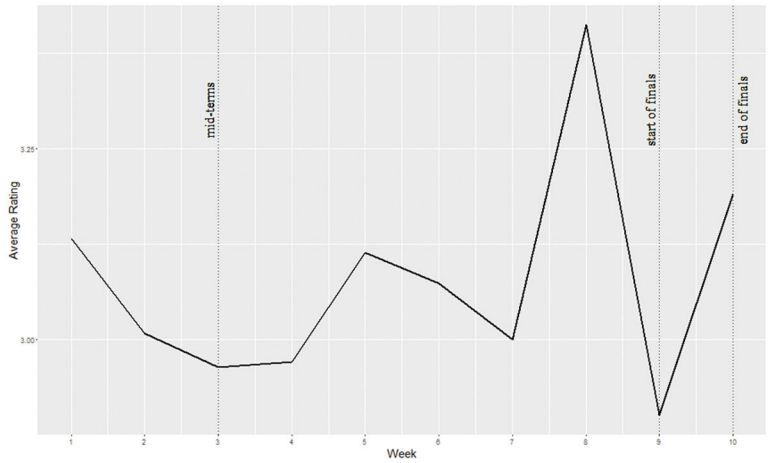

Figure 2.

Average Sleep Rating for Freshmen Students at the University of California, Los Angeles During the Fall Semester 2015 (n = 181), Los Angeles, CA 15 (n = 181), Los Angeles, CA

Table 1

Demographic Characteristics of Freshmen Students (n = 181).*

Category	Total	%
Gender		
Female	109	60.22
Male	70	38.67
Transgender	1	0.55
Genderqueer	1	0.55
Ethnicity		
Asian	48	26.52
Black Non-Hispanic	21	11.60
Hispanic	53	29.28
White Non-Hispanic	39	21.55
American Indian or Alaskan Native	1	0.55
Multiracial	11	6.08
Other**	8	4.42
Age		
17	5	2.76
18	154	85.08
19	16	8.84
20	6	3.31
Average:	18.1	
School Major		
Business	15	8.29
Health Science/Biology	77	42.54
Science/Math/Engineering	23	12.71
Social Sciences/Arts	41	22.65
Undeclared	25	13.81

* Total Number of Observations across all 10 Weeks: 1,550

** Students of multiple ethnicities and nationalities

Total Number of Observations by week: Week 1: 132, Week 2: 128, Week 3: 171, Week 4: 174, Week 5: 167, Week 6: 172, Week 7: 157, Week 8: 160, Week 9: 146, Week 10: 148

Table 2

Summary Twitter Data for Freshmen Students (n=166)

Summary Data		
Tweets and retweets	**Total**	**%**
Total Tweets + Retweets	35,945	-
Total Tweets	21,491	59.79%
Total Retweets	14,454	40.21%
Activity by day of the week	**Total**	**%**
Monday	5440	15.13%
Tuesday	5677	15.79%
Wednesday	5640	15.69%
Thursday	5400	15.02%
Friday	4513	12.56%
Saturday	3951	10.99%
Sunday	5324	14.81%
Activity by weekday vs. weekend	**Total**	**%**
Weekdays (Mon–Thu)	22157	61.64%
Weekends (Fri–Sun)	13788	38.36%
Activity by time of day	**Total**	**%**
Morning/Noon (from 7am to 1pm)	7370	20.50%
Afternoon (from 1pm to 7pm)	11069	30.79%
Evening (from 7pm to 2am)	15985	44.47%
Late Night (from 2am to 6am)	1521	4.23%
Length of tweets (# of elements in a tweet)	**Min**	**Max**
Quartile 1 (short tweets)	0	4
Quartile 2	5	8
Quartile 3	9	13
Quartile 4 (long tweets)	14	45
Prevalence of emotions		
Emotion	**Handcoded Rate**	**Predicted Rate**
Anger	7.71%	9.90%
Fear	17.04%	12.43%
Love	12.24%	12.24%
Joy	22.09%	18.71%
Neutral	25.75%	19.05%

Inf Commun Soc. Author manuscript; available in PMC 2019 January 01.

Table 3

Generalized Linear Mixed Model (GLMM) – Modelling Weekly Sleep Quality and Twitter Use for Freshmen Students.

Section A: Tweeting Time of Day					
	Time of Day (Proportion of Weekly Tweets that are:)	**B**	**SE**	**AIC**	**BIC**
Weekdays[1]	Morning	0	0.111	3177	3269
	Afternoon	−0.12	0.102	3175	3268
	Evening	0.189*	0.097	3173	3266
	Late Night	−.937**	0.352	3167	3260
Weekends[1]	Morning	0.167	0.135	3175	3268
	Afternoon	−0.186	0.111	3174	3267
	Evening	0.1	0.116	3176	3269
	Late Night	−0.342	0.342	3173	3266
Section B: Characteristics of Weekday Tweets		**B**	**SE**	**AIC**	**BIC**
	Short Tweets				
Proportion of tweets during each time period that are short[1]:	Morning	0.017	0.084	3177	3270
	Afternoon	0.041	0.082	3177	3270
	Evening	−0.117	0.08	3175	3268
	Late night	−.413**	0.139	3167	3260
	Long Tweets				
Proportion of tweets during each time period that are long[1]:	Morning	0.066	0.08	3177	3269
	Afternoon	−0.024	0.08	3177	3270
	Evening	.197*	0.087	3172	3265
	Late night	−0.025	0.137	3176	3269
	Emotions				
Proportion of tweets that are a given emotion[2]:	Angry	−0.205	0.169	3013	3106
	Fearful	−0.302*	0.131	3011	3102
	Loving	0.026	0.138	3016	3108
	Joyful	0.105	0.128	3015	3107
	Neutral	−0.135	0.131	3015	3107

[1]: Total Number of Observations: 1,295, Total Number of Individuals: 166

[2]: Total Number of Observations: 1,229, Total Number of Individuals: 165

* $P < 0.05$,

** $P < 0.01$