Title: Temporal association between objectively-measured smartphone usage, sleep quality, and physical activity among Chinese adolescents and young adults

Running title: Smartphone, sleep, and physical activity

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ABSTRACT

We studied the association between objectively-measured smartphone usage and objectively-measured sleep quality and physical activity for seven consecutive days among Hong Kong adolescents and young adults aged 11-25 (n=357, 67% female). We installed an app that tracked the subjects' smartphone usage and had them wear an ActiGraph GT3X accelerometer on their wrist to measure their sleep quality and physical activity level. Smartphone usage data were successfully obtained from 187 participants (52.4%). The participants on average spent 2 hours 46 minutes per day on their smartphone. Multilevel regression showed that one minute of daytime smartphone usage was associated with 0.07 minute decrease in total sleeping time that night (p=0.043, 95% CI: -0.14, -0.003). Broken down for different usage purposes, one minute of daytime social network usage and games and comics was associated with a 0.28 (p=0.02, 95% CI: -0.52, -0.04) minute and 0.18 minute (p=0.01, 95% CI: -0.32, -0.04) decrease in total sleeping time that night, respectively. One minute of daytime smartphone usage was associated with 4.55 steps increase in the number of steps (p=0.001, 95% CI: 1.77, 7.34) on the next day. To conclude, time spent on smartphone at daytime was associated with total sleeping time that night and number of steps next day, but was not associated with sleep efficiency, wake after sleep onset, and MVPA among Hong Kong adolescents and young adults.

Keywords: exercise; gaming; screen; smart device; smartphone monitoring; youth

1.INTRODUCTION

The use of smartphones has been increasing rapidly in recent years. The number of smartphone users worldwide was 1.5 billion in 2014 and this figure is expected to be doubled in 2020 (Statistista, 2015). Smartphones have substituted for mp3 music players, video players, and handheld game consoles, as they allow easy access to all of these functions at any time and any place at the user's convenience (Kwon, Kim, Cho, & Yang, 2013). Smartphones also allow for the taking of instant photos and videos and the sharing of them through the internet. Moreover, smartphones allow users to download attractive and powerful applications for education, entertainment, and stock transactions. Smartphones are becoming so important that 29% of their owners "can't imagine living without" them (Pew Research Center, 2015).

Smartphone ownership and usage are a global phenomenon, with Hong Kong being one of the cities with the highest penetration rates around the world (ranked 8^{th} out of 47 countries or places in 2013 (Mashable, 2013)). Local studies have revealed that almost all adults, more than 50% of primary school students, and more than 90% of secondary school students possess at least one smartphone (HKSARG Department of Health, 2015). Another study conducted by the Hong Kong Polytechnic University showed that 30% of school students used smart devices (including smartphones and tablets) for one to four hours per day (Hong Kong Polytechnic University Department of Physiotherapy, 2013).

While appropriately using smartphones can improve our quality of life, excessive usage can possibly lead to adverse health outcomes. The excessive usage of smartphones was associated with sedentary lifestyles (Lepp, Barkley, Sanders, Rebold, & Gates, 2013), poor sleeping habits (Punamaki, Wallenius, Nygard, Saarni, & Rimpela, 2007), and increased waking-time tiredness (Punamaki et al., 2007). A recent large-scale cross-sectional study among adolescents in Norway showed that both the daytime and bedtime use of electronic devices was associated with sleep problems (Hysing et al., 2015), confirming the theoretical pathway that the lighted screen of smartphone suppresses melatonin and affects sleep. Furthermore, increased time spent in bedtime smartphone usage will shorten the user's total sleeping time, and the resulted tiredness may reduce time spent in physical activity the next day.

Note that all of the aforementioned studies suffered a common major limitation, namely the cross-sectional nature that the possibility of reverse causation (that is, sleep quality causing smartphone usage) could not be eliminated, the use of the self-report level of smartphone usage, in which the reporting was subjected to recall bias (Hysing et al., 2015), unknown validity and reliability (Hysing et al., 2015), and an inability to track the frequently-changing smartphone usage habit (Benson et al., 2013).

Objectively-measured data on smartphone usage can be obtained by directly monitoring smartphone activities. Many smartphone monitoring applications have been written, most of which have been aimed at collecting usage information on data transfer and battery power consumption for further hardware development and improvement (Bohmer, Hecht, Schoning, Kruger, & Bauer, 2011; Do, Blom, & Gatica-Perez, 2011; Falaki, Mahajan, & Estrin, 2011; Falaki et al., 2010; Shye, Scholbrock, Memik, & Dinda, 2010; Soikkeli, Karikoski, & Hammainen, 2011). Very few studies have correlated objectively-measured smartphone usage with other outcomes; to the best of our knowledge, there exists only one study correlating objectively-measured smartphone usage with personality traits (Chittaranjan, Blom, & Gatica-Perez, 2013). To date, there have been no studies on the association between objectively-measured smartphone usage and health outcomes. Here, we studied the temporal association between objectively-measured smartphone usage in a day, the accelerometer-measured sleep quality that night, and the accelerometer-measured physical activity the next day measured for seven consecutive days in Hong Kong Chinese adolescents and young adults. Furthermore, to complete the examination of the possible bidirectional association between smartphone usage and sleep quality, we also studied the temporal association between the accelerometer-measured sleep quality in a night and the objectively-measured daytime smartphone usage in the next day.

2.METHODS

2.1.Participants

This study was conducted from March 2017 to May 2018. The participants were recruited from one secondary school (Tai Po Sam Yuk Secondary School, which corresponds to Years 7 to 12 in the US education system) and two universities (Hong Kong Polytechnic University and Education University of Hong Kong) in Hong Kong. In the secondary school, invitation letters were sent to the parents of all students. In the two universities, invitation emails were sent to all undergraduate students. Only those aged 11-25, who were able to speak and read Chinese, and owned a smartphone with the Android operating system were recruited to take part in this study. Phones with the Apple iOS operating system were excluded because Apple iOS app programmers are not allowed to collect smartphone usage data continuously. Written consent was obtained from all of the participants. For participants under the age of 18, parental written consent was also obtained. As a token of appreciation, a supermarket cash coupon worth HK $100 (approximately US $13) was given to the participants after the data were collected. This study was approved by the Human Subjects Ethics Sub-Committee of the Hong Kong Polytechnic University.

2.2.Data collection

2.2.1.Objectively-measured smartphone usage. We installed a smartphone usage tracking app (created by our team) on the smartphone of all of the participants' smartphone for seven consecutive days. This app tracked the opening and closing of all apps in the smartphone. No private or personal data, such as the contents of instant messages and the web pages that were browsed, were collected. For those participants who possessed more than one smartphone, we installed the app in their most commonly-used phone. We defined an app as being used when it was running in the graphical interface. It should be noted that the opening of one app would trigger the closure of the app currently being used, if any. The usage time was tracked by seconds. The names of the apps being used, their opening time, and closing time were stored in the smartphone and uploaded to a remote server (Firebase) once internet connection was available, and all uploaded data were removed from the smartphone.

2.2.2.Sleep quality and physical activity level. During the seven-day monitoring period, all of the participants concurrently wore an ActiGraph GT3X accelerometer. This is a wrist-worn, water-proof accelerometer that has been validated for measuring sitting time (Ryde, Gilson, Suppini, & Brown, 2012), physical activity (Pfitzner et al., 2013). and sleeping time.(P. H. Lee & Suen, 2017; Toon et al., 2016) The participants were instructed to wear the accelerometer on their non-dominant hand for 24 hours a day over seven consecutive days. They were asked to record the removal time in a logbook, if any (for example, when accelerometer might become damaged). Data were collected in 1-minute epoch. To synchronize the accelerometer data with smartphone usage data, when initializing the accelerometers Greenwich Mean Time +8, obtained via the internet, were used.

2.3.Data processing

2.3.1.Sleep quality and physical activity level. Peak acceleration in the three axes was extracted from the raw acceleration. The resultant acceleration of the raw acceleration from three axes was summarized by counts per minute (CPM). CPM of $\geq$4,514 of the vector magnitude was classified as moderate-to-vigorous-intensity activity (MVPA) (calibrated among Hong Kong young adults (P. H. Lee & Tse, 2019)). Non-wearing time was defined as consecutive zero counts for 60 or more minutes. The amount of wearing time in a day was computed by subtracting the non-wearing time and sleeping time (determined by the accelerometer) from 24 hours. A valid day must include at least 10 hours of wearing time excluding sleeping time. Steps were detected using the built-in algorithm of the ActiGraph that based on the acceleration amplitude and frequency (John, Morton, Arguello, Lyden, & Bassett, 2018). Steps accumulated in time length of <10 seconds were removed by the ActiGraph. As we used a temporal analysis that treated a day as the unit of analysis and did not require the averaging of PA and sleep parameters of individual participants throughout the whole study period, participants who provided at least one valid day could be included in the analysis.

All of the minutes recorded from the accelerometers were classified as either sleep or awake using Sadeh's algorithm (Sadeh, Sharkey, & Carskadon, 1994). According to Sadeh's algorithm, the sleep index of a minute is defined as 7.601 – (0.065×AVG) – (1.08×NATS) – (0.056×SD) – (0.703×LG), where AVG is the average CPM of the 11 minutes centered at the current minute, NATS is the number of minute with CPM between 50 to 99 at the 11-min period, SD is the standard deviation of the current and five preceding minutes, and LG is the natural log of the CPM+1 (to avoid log of 0) at the current minute. Recorded minutes with sleep index of ≥-4 will be classified as sleep, and awake otherwise. Sleep onset was defined as the first 15 minutes of consecutive sleeping minutes, and awakening time was defined as the first 15 minutes of consecutive wake minutes. The total sleeping period was measured as beginning at sleep onset and ending at awakening. Total sleeping time was defined as the sleeping time within the total sleeping period. Sleep efficiency was defined as the total sleeping time divided by the total sleeping period. Wake after sleep onset (WASO) was defined as the waking time within the total sleeping period.

2.3.2Objectively-measured smartphone usage. All recorded smartphone applications were categorized under social network (Facebook, Twitter, Instagram, Weibo, etc.), instant messaging (Whatsapp, Skype, Line, Wechat, etc.), web browsing (including browser and apps developed for browsing specific websites), games and comics (except games plug-ins and guides), multimedia (related to music, video, and image/photo, for example YouTube and MOOV), camera (including beauty-themed photo and video apps such as Meitu), and health (pedometer, GPS distance and speed tracker, etc.). The time spent on each usage session was computed as the difference between the closing time and opening time. Usage sessions of less than 1 second were discarded as such short times were likely to be an indication that the app had been accidentally pressed. All smartphone usage time were classified as either occurring in the daytime (defined as the time from waking up to 1 hour before sleep, where the sleeping time was identified using the accelerometer data), bedtime (defined as 1 hour before sleep), or during wakeful moment at sleep (or WASO).

2.4.Statistical analysis

Descriptive statistics (mean, SD, frequency) were used to summarize the pattern of smartphone usage, sleep quality, and physical activity level. Multilevel regression was used to examine the temporal association between daytime and bedtime smartphone usage with sleep quality that night and physical activity on the following day, adjusted for the data source (secondary school / university), sex, and within-subject correlation. The within-subject correlation was assumed to have an auto-regressive structure of order one (or AR(1)). The same model was also used to examine the temporal association between the sleep quality and the daytime smartphone usage on the following day. The intra-class correlation (ICC), auto-correlation, and R^2 of all models were reported. The data from the first day that the smartphone usage tracking app was installed and the accelerometer was distributed were excluded due to the incompleteness of the data. All data were analyzed both among the overall sample and stratified by school type (secondary school versus university). Histograms of the residuals and residual plots were used to examine the assumptions of multilevel regression, including normality, homoscedasticity, and independence of observations. A *p*-value of <0.05 was considered significant, and multiple comparisons were not controlled because of the high number of correlated null hypotheses in this study (Moran, 2003).

3.RESULTS

A total of 393 students (156 from the secondary school and 237 from the two universities) agreed to participate, and 357 of them who provided at least one valid day of accelerometer data were included in the current analysis. Table 1 shows the characteristics of the participants. Nearly two-thirds of them were university students. The secondary school sample was balanced in gender, but in the university sample less than one-fourth of them were male. The sleep quality and physical activity level of the two samples were comparable.

[Table 1 inserted here]

Of the 357 participants, smartphone usage data were successfully tracked for 187 (52.4%). The smartphone tracking app was written for Android 7.0 or above, and the tracking app did not work with some smartphones installed with earlier Android versions. The daytime and bedtime smartphone usage data are summarized in Table 2. The participants spent nearly 3 hours per day on their smartphone. Secondary school students on average spent 40 more minutes per day on smartphones than university students. The most common type of usage among secondary school students and university students were games and comics apps (1 hour 30 minutes per day) and instant messaging apps (1 hour 13 minutes per day), respectively. Bedtime smartphone usage was recorded in 464 (42.0%) out of the 1,106 measured nights. On average the participants spent 10 minutes per day on their smartphone during bedtime. Smartphone usage during WASO was recorded in 563 (50.9%) out of the 1,106 measured nights. On average the participants spent 29 minutes per day on their smartphone during WASO.

[Table 2 inserted here]

Table 3 shows the multilevel regression results of smartphone usage on sleep quality. Results among the overall sample showed that one minute of daytime smartphone usage was associated with 0.07 minute decrease in total sleeping time that night (p=0.043, 95% CI: -0.14, -0.003). Broken down for different usage purposes, one minute of daytime social network usage and games and comics was associated with a 0.28 (p=0.02, 95% CI: -0.52, -0.04) minute and 0.18 minute (p=0.01, 95% CI: -0.32, -0.04) decrease in total sleeping time that night, respectively. Daytime smartphone usage was not associated with sleep efficiency and WASO. One minute of bedtime social network usage was associated with 2.58 minute increase in total sleeping time that night (p=0.01, 95% CI: 0.60, 4.36). One minute of web browsing during WASO was associated with 2.29 minute increase in total sleeping time (p=0.047, 95% CI: 0.03, 4.55) and 0.46 minute of WASO (p=0.02, 95% CI: 0.08, 0.83) that night. Among secondary school students, one minute of daytime smartphone usage was associated with 0.12 minute decrease in total sleeping time that night (p=0.042, 95% CI: -0.23, -0.007). Broken down for different usage purposes, only social network (β=-0.39, p=0.03, 95% CI: -0.73, -0.04) was associated with total sleeping time. One minute of bedtime smartphone usage was associated with 0.32 minute increase in wake after sleep onset that night (p=0.04, 95% CI: 0.02, 0.62). One minute of smartphone usage during WASO was associated with sleep efficiency (β=0.013%, p=0.01, 95% CI: 0.003%, 0.023%) and WASO (β=-0.05, p=0.04, 95% CI: -0.10, -0.005). Among university students, smartphone usage during daytime, bedtime, and sleep were insignificantly associated with sleep quality. Broken down for different usage purposes, daytime tools usage (β=0.32, p=0.02, 95% CI: 0.04, 0.60) and bedtime social network usage (β=2.38, p=0.02, 95% CI: 0.37, 4.39) was associated with total sleeping time, while instant messaging (β=0.04, p=0.048, 95% CI: 0.001, 0.07), web browsing (β=0.47, p=0.02, 95% CI: 0.09, 0.84), and camera usage (β=25.79, p=0.01, 95% CI: 6.22, 45.36) during WASO were associated with WASO.

[Table 3 inserted here]

Table 4 shows the multilevel regression results of smartphone usage on physical activity level. One minute of daytime smartphone usage was associated with 7.15 steps increase in the number of steps (p=0.02, 95% CI: 1.02, 13.28) among secondary school students, 3.52 steps increase in the number of steps (p=0.03, 95% CI: 0.37, 6.66) among university students, and 4.55 steps increase in the number of steps (p=0.001, 95% CI: 1.77, 7.34) in the overall sample on the next day. Social network, instant messaging, tools, multimedia usage, and total smartphone usage (β=0.06, p=0.01, 95% CI: 0.01, 0.11) were positively associated with both the number of steps and the time spent on MVPA in the overall sample. Smartphone usage during bedtime and sleep were insignificantly associated with physical activity level, except web browsing during WASO was associated with number of steps (β=1153.07, p=0.04, 95% CI: 57.92, 2248.22) among secondary school students.

[Table 4 inserted here]

Table 5 shows that, for both secondary school students and university students, better sleep quality was associated with higher volume of physical activity level on the next day, except that one percent increase in sleep efficiency was associated with 112.44 step decrease (*p*=0.02, 95% CI: 12.55, 212.33) among secondary school students. Table 6 shows that all associations between sleep quality and daytime smartphone usage were insignificant except one percent increase in sleep efficiency was associated with 9.42 second decrease in time spent on web browsing the next day (*p*=0.02, 95% CI: -17.50, -1.33) among university students.

[Table 5 inserted here]

[Table 6 inserted here]

Histograms of the residuals and residual plots of all regressions are shown in Supplementary Figures S1 to S72. Overall speaking, the residuals were normal (except for sleep efficiency that was slightly skewed to the left), homoscedastic, and independent of each other.

The ICC, auto-correlation, and R2 of all multilevel regression models could be found in Supplementary Tables S1 to S4. The overall sample showed a small ICCs of 0.10-0.12 on total sleeping time and 0.14-0.15 on the number of steps, while the ICCs were of moderate size for ICC of sleep efficiency (0.27-0.28), WASO (0.26-0.27), and MVPA (0.30-0.31). The auto-correlation showed that the sleeping variables were only slightly auto-correlated among both secondary school students and university students, while the physical activity variables had a small-to-moderate auto-correlation. The difference between ICC and R^2 of the models showed that the independent variables (data source, gender, and smartphone usage) explained 7-10% on total sleeping time and 9-12% on sleep efficiency WASO, number of steps, and time spent on MVPA. In sum, the within-subject effect explained a larger proportion of variance than the between-subject effect for all sleep and PA variables.

4.DISCUSSION

We conducted a study to examine the association between objectively-measured smartphone usage, sleep quality, and physical activity level among Hong Kong Chinese adolescents and young adults. We found that the explanatory power of total smartphone usage on sleep quality among secondary school students, university students, and overall sample was 3.14%-5.89%, 0.16%-0.34%, and 0.02%-0.52%, respectively (Supplementary Table S5). We concluded that the explanatory power of smartphone usage on sleep among university students was negligible (with similar explanatory power among US children (Przybylski, 2019)), while smartphone usage was a significant contributor of sleep, in particular total sleeping time, among secondary school students. There were several advantages to using the objective measurement of smartphone usage. First, we could identify different purposes for which smartphone was being used, and showed the effect of smartphone use on different aspects of life. For instance, we found that only the use of social network apps and games and comics apps was associated with total sleeping time. Second, together with sleeping parameters objectively measured with accelerometer, we could define sleeping time and bedtime smartphone usage objectively, and exclude the possibility of reverse causation that sleep quality has a negligible effect on smartphone usage the next day. Note that our data did not rule out (and could not identify) the complex, bidirectional nature between sleep pattern and smartphone usage during sleep, whereby people with sleep problems would use their smartphone during bedtime as a way of spending their energy (Przybylski, 2019), and in turn the blue light emission from smartphone will suppress melatonin secretion that further delay sleep onset (Figueiro & Overington, 2016). Third, while the validity of self-reported smartphone usage was questionable, the source of measurement error could be eliminated through objective measurement of smartphone usage.

In studies on the association between smartphone usage and sleep quality, most used a self-reported questionnaire to measure sleep quality and only three studies measured sleep quality with a wrist-worn accelerometer (Cabré-Riera et al., 2019; Fobian, Avis, & Schwebel, 2016; Murdock, Horissian, & Crichlow-Ball, 2016). Surprisingly, all three studies found no association. On the one hand, the finding of a null association might be a true finding; on the other hand, it is possible that these studies committed a type II error because the sample sizes ranged from 55 to 110 only. Furthermore, in these studies, smartphone usage data were not collected in a daily manner and only the averaged accelerometer-measured sleep quality across the measurement period could be used, so that the within-subject variation was ignored. With a repeated measure of 814 nights in a study involving 187 subjects that both within-subject and between-subject variation could be examined, ours has the largest in sample size and showed that both daytime and bedtime smartphone usage were associated with total sleeping time but not with sleep efficiency and WASO.

Several researchers attempted to differentiate between the physiological effects of daytime and bedtime smartphone usage. Compared to other devices with electronic screens such as televisions and video game consoles, the smartphone is more commonly used in bed as they are portable and are usually placed very close to the user (Twenge, Hisler, & Krizan, 2019; Wood, Rea, Plitnick, & Figueiro, 2013). To the best of our knowledge, all existing studies have relied on self-reported data to determine bedtime smartphone usage. As the validity of self-reports of bedtime smartphone usage requires the accurate recalling of both bedtime and smartphone usage, we questioned the validity of self-report and used objective measure of sleep onset and smartphone usage to determine bedtime smartphone usage. The invalidity of self-reported bedtime smartphone usage is shown by the disagreement of our results with other existing self-reported results; for example a Taiwanese study using self-reported data showed that bedtime smartphone usage was very common (95%) among junior college students (Wang, Chen, Yang, & Lin, 2019), but the current study recorded such usage in less than half of the nights (42.4%). Our results also highlighted the importance of distinguishing between daytime and bedtime smartphone usage, as total sleeping time was negatively related to daytime usage but not related to bedtime usage. We found no association between smartphone usage, both daytime and bedtime, and sleeping efficiency, and these results did not agree with some previous findings (Amra et al., 2017; Carter, Rees, Hale, Bhattacharjee, & Paradkar, 2016; Lemola, Perkinson-Gloor, Brand, Dewald-Kaufmann, & Grob, 2015; Mireku et al., 2019). We believe that the effects of smartphone usage and sleep outcomes are still controversial (some other studies found a null association (Demirci, Akgönül, & Akpinar, 2015)) and warrant further investigations, especially through employing well-designed controlled trials. We suspect that, in previous studies, participants might mixed up bedtime smartphone usage and usage during WASO, as we found that smartphone usage during WASO did improve sleep efficiency. To the best of our knowledge, very few randomized controlled trials have been conducted in this direction, and some found a null association between smartphone usage and sleep outcomes due to small sample size (Dunican et al., 2017).

Besides the time of use, the purpose for which a smartphone is used may also have an impact on sleep outcomes. This study found that only using a smartphone for social network apps and games and comics apps, but not for other types of apps, was associated with total sleeping time. It was hypothesized that interactive smartphone use should have stronger effects on sleep than the passive viewing of a smartphone screen (Dworak, Schierl, Bruns, & Struder, 2007). Our results only partially agreed with this hypothesis. Social network app usage can be regarded as passive viewing as its use does not involve frequent touching of the phone. However, the contents of social network are updated extremely quickly and new updates can be expected to occur every minute. Therefore, users may be anxious about missing out on new content, and such anxiety may cause users to stay awake during the night (Woods & Scott, 2016). Yet, some studies found that social network use was, in fact, positively related to sleep quality (Nursalam, Octavia, Tristiana, & Efendi, 2019), partially because social network sites can help users to connect, make new friends, and share their stress (Nursalam et al., 2019). In addition to social network apps, instant messaging apps were also commonly used among our subjects, and we found no association between its use and all sleep outcomes. It was hypothesized that it is difficult to leave a discussion initiated through instant messaging, which thereby delays sleep onset. This hypothesis was supported by the fact that texting was negatively associated with sleep quality (Exelmans & Van den Bulck, 2016) and its effect on sleep duration was the strongest among other electronic screen usages (Yland, Guan, Emanuele, & Hale, 2015). However, we questioned the validity of these results as they relied on self-reported time spent on instant messaging and such data, being recalled data, is inherently unreliable. Our data showed that instant messaging apps were used frequently, at an average of 363.7 times per day and that each session only lasted for an average of 26 seconds. We believe that the frequent and short usage nature of instant messaging apps made the recalling of time spent on them challenging.

It was generally expected that the use of a smartphone would lead to a sedentary and inactive lifestyle due to its sedentary nature (Kenney & Gortmaker, 2017; Lepp et al., 2013). Surprisingly, our data showed that social network, instant messaging, tools, and multimedia app usage at daytime were all positively associated with physical activity level. We believe that there was a bi-directional causation. Those who were more physically active might have spent more time on social network and instant messaging apps to share their photos and information. Similarly, some of the multimedia app usage might have been occurred concurrently with physical activity (e.g., playing a video during jogging on a treadmill). On the other hand, our data found no association between games and health app usage and physical activity level. Recently, some augmented reality games developed for smartphone have encouraged walking in the real world (e.g., Pokémon GO), and there is evidence to show that their use is promoting engagement in physical activity (Howe et al., 2016; Wong, 2017). In the current study, too few subjects played Pokémon GO (11 out of 187, 5.9%); therefore, the health-promoting effect of this kind of augmented reality game might have been diluted by the sedentary effect of other kinds of games. Similarly, users of health-related apps, for instance pedometer apps, were found to be physically more active than non-users (Carroll et al., 2017; Ernsting et al., 2017). In the current study, too few subjects used health-related apps (31 out of 187, 16.6%); less than the previously reported percentage (34.1%) in a US sample (Carroll et al., 2017). Most importantly, no secondary school students in our sample used any kind of health-related apps during the measurement period, therefore, we were unable to detect the associations between the usage of health-related apps, sleep quality, and physical activity level.

The major limitation of this study lied in the area of sampling and data collection. Only Android users were recruited in this study and cautions should be taken when our results are generalized to users of other smartphones. This also explains the small number of adolescent participants in our sample; most of the students in our recruited secondary schools were using an iPhone that is not supported by our tracking app. Nonetheless, our sample has comparable smartphone usage level (206 min/day) with Korean college students (210 min/day) (U. Lee et al., 2014) and US adults (159 min/day) (Deng et al., 2019). In our sample, about 10% of the participants owned more than one smartphone. Since the smartphone usage tracking app was only installed in one smartphone of the subjects, we might have underestimated the total smartphone usage. Another limitation was that our smartphone tracking app could not record the usage of some Android default system apps, for example Google Chrome, the default web browser of Android system, in some versions of Android operating system. It only affected the measurement of time spent on web browsing but not on the other usage types. A minor limitation was that different recruitment approach was used in secondary school and universities that might affect the generalizability of our results. It is known that monitoring of PA level with accelerometers could lead to an increase in PA among older adults (Cooper et al., 2018), but the monitoring has no impact among adolescents (Vanhelst, Béghin, Drumez, Coopman, & Gottrand, 2017). To the best of our knowledge, we were unable to identify any studies that examine the impact of wearing an accelerometer on sleep quality among adolescents, therefore we could not determine its impact in our sample. Smartphone usage time during WASO was subjected to error as the phone usage may not be performed by the smartphone owner, or the actual waking time was misclassified as sleep by the ActiGraph (Kushida et al., 2001).

5.CONCLUSIONS

Time spent on social network apps and games and comics apps at daytime, social network apps at bedtime, and web browsing apps during WASO was associated with total sleeping time. Time spent on social network apps, instant messaging apps, and multimedia apps at daytime were associated with the number of steps and MVPA among Hong Kong Chinese adolescents and young adults. All other types of smartphone usage were not associated with sleep quality and physical activity. The study design could not infer causality and further investigations on these effects employing experimental designs are warranted.

Availability of data and materials

The dataset(s) supporting the conclusions of this article is(are) available upon request.

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Competing interests

The authors declare that there are no known conflicts of interest associated with this publication.

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REFERENCES

Amra, B., Shahsavari, A., Shayan-Moghadam, R., Mirheli, O., Moradi-Khaniabadi, B., Bazukar, M., . . . Kelishadi, R. (2017). The association of sleep and late-night cell phone use among adolescents. *J Pediatr (Rio J), 93*(6), 560-567.

Benson, V. S., Pirie, K., Schuz, J., Reeves, G. K., Beral, V., Green, J., & for the Million Women Study Collaborators. (2013). Mobile phone use and risk of brain neoplasms and other cancers: prospective study. *Int J Epidemiol, 42*(3), 792-802.

Bohmer, M., Hecht, B., Schoning, J., Kruger, A., & Bauer, G. (2011). *Falling asleep with Angry Birds, Facebook and Kindle - A large scale study on mobile application usage.* Paper presented at the MobileHCI 2011, Stockholm, Sweden.

Cabré-Riera, A., Torrent, M., Donaire-Gonzalez, D., Vrijheid, M., Cardis, E., & Guxens, M. (2019). Telecommunication devices use, screen time and sleep in adolescents. *Environ Res, 171*, 341-347.

Carroll, J. K., Moorhead, A., Bond, R., LeBlanc, W. G., Petrella, R. J., & Fiscella, K. (2017). Who uses mobile phone health apps and does use matter? A secondary data analytics approach. *J Med Internet Res, 19*(4), e125.

Carter, B., Rees, P., Hale, L., Bhattacharjee, D., & Paradkar, M. (2016). Association between portable screen-based media device access or use and sleep outcomes: A systematic review and meta-analysis. *JAMA Pediatr, 170*(12), 1202-1208.

Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2013). Mining large-scale smartphone data for personality studies. *Pers Ubiquit Comput, 17*(3), 433-450.

Cooper, C., Gross, A., Brinkman, C., Pope, R., Allen, K., Hastings, S., . . . Goode, A. P. (2018). The impact of wearable motion sensing technology on physical activity in older adults. *Exp Gerontol, 112*, 9-19.

Demirci, K., Akgönül, M., & Akpinar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *4, 2*(85-92).

Deng, T., Kanthawala, S., Meng, J., Peng, W., Kononova, A., Hao, Q., . . . David, P. (2019). Measuring smartphone usage and task switching with log tracking and self-reports. *Mobile Media Commun, 7*(1), 3-23.

Do, T. M. T., Blom, J., & Gatica-Perez, D. (2011). *Smartphone usage in the wild: a large-scale analysis of applications and context.* Paper presented at the ICMI'11, Alicante, Spain.

Dunican, I. C., Martin, D. T., Halson, S. L., Reale, R. J., Dawson, B. T., Caldwell, J. A., . . . Eastwood, P. R. (2017). The effects of the removal of electronic devices for 48 hours on sleep in elite judo athletes. *J Strength Cond Res, 31*(10), 2832-2839.

Dworak, M., Schierl, T., Bruns, T., & Struder, H. K. (2007). Impact of singular excessive computer game and television exposure on sleep patterns and memory performance of school-aged children. *Pediatrics, 120*(5), 978-985.

Ernsting, C., Dombrowski, S. U., Oedekoven, M., O'Sullivan, J. L., Kanzler, M., Kuhlmey, A., & Gellert, P. (2017). Using smartphones and health apps to change and manage health behaviors: A population-based survey. *J Med Internet Res, 19*(4), e101.

Exelmans, L., & Van den Bulck, J. (2016). Bedtime mobile phone use and sleep in adults. *Soc Sci Med, 148*, 93-101.

Falaki, H., Mahajan, R., & Estrin, D. (2011). *SystemSens: A tool for monitoring usage in smartphone research deployments.* Paper presented at the MobiArch'11, Bethesda, Maryland, USA.

Falaki, H., Mahajan, R., Kandula, S., Lymberopoulos, D., Govindan, R., & Estrin, D. (2010). *Diversity in smartphone usage.* Paper presented at the MobiSys'10, San Francisco, California, USA.

Figueiro, M., & Overington, D. (2016). Self-luminous devices and melatonin suppression in adolescents. *Lighting Res Technol, 48*, 966-975.

Fobian, A. D., Avis, K., & Schwebel, D. C. (2016). The impact of media use on adolescent sleep efficiency. *J Dev Behav Pediatr, 37*(1), 9-14.

HKSARG Department of Health. (2015). Health Effects on Use of Internet and Electronic Screen Products. Retrieved Sep 4, 2015, from http://www.studenthealth.gov.hk/english/internet/health_effects.html

Hong Kong Polytechnic University Department of Physiotherapy. (2013). A survey on health effects of the use of smart phones and related electronic products in Hong Kong [Press release]

Howe, K. B., Suharlim, C., Ueda, P., Howe, D., Kawachi, I., & Rimm, E. B. (2016). Gotta catch’em all! Pokémon GO and physical activity among young adults: difference in differences study. *BMJ, 355*, i6270.

Hysing, M., Pallesen, S., Stormark, K. M., Jakobsen, R., Lundervold, A. J., & Sivertsen, B. (2015). Sleep and use of electronic devices in adolescence: results from a large population-based study. *BMJ Open, 5*, e006748.

John, D., Morton, A., Arguello, D., Lyden, K., & Bassett, D. (2018). “What Is a Step?” Differences in How a Step Is Detected among Three Popular Activity Monitors That Have Impacted Physical Activity Research. *Sensors, 18*(4), 1206.

Kenney, E. L., & Gortmaker, S. L. (2017). United States adolescents' television, computer, videogame, smartphone, and tablet use: Associations with sugary drinks, sleep, physical activity, and obesity. *J Pediatr, 182*, 144-149.

Kushida, C., Chang, A., Gadkary, C., Guilleminault, C., Carrillo, O., & Dement, W. C. (2001). Comparison of actigraphic, polysomnographic, and subjective assessment of sleep parameters in sleep-disordered patients. *Sleep Med, 2*(5), 389-396.

Kwon, M., Kim, D. J., Cho, H., & Yang, S. (2013). The Smartphone Addiction Scale: Development and validation of a short version for adolescents. *PLoS One, 8*(12), e83558.

Lee, P. H., & Suen, L. K. P. (2017). The convergent validity of Actiwatch 2 and ActiGraph Link accelerometers in measuring total sleeping period, wake after sleep onset, and sleep efficiency in free-living condition. *Sleep Breath, 21*(1), 209-215.

Lee, P. H., & Tse, A. C. Y. (2019). Calibration of Wrist-worn ActiWatch 2 and ActiGraph wGT3X for Assessment of Physical Activity in Young Adults. *Gait Posture, 68*, 141-149.

Lee, U., Lee, J., Ko, M., Lee, C., Kim, Y., Yang, S., . . . Song, J. (2014). *Hooked on* *smartphones: an exploratory study on smartphone overuse among college students*. Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems New York.

Lemola, S., Perkinson-Gloor, N., Brand, S., Dewald-Kaufmann, J. F., & Grob, A. (2015). Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. *J Youth Adolescence, 44*, 405-418.

Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *Int J Behav Nutr Phys Act, 10*, 79.

Mashable. (2013). The 15 Countries With the Highest Smartphone Penetration. Retrieved 9 May, 2019, from https://mashable.com/2013/08/27/global-smartphone-penetration/

Mireku, M. O., Barker, M. M., Mutz, J., Dumontheil, I., Thomas, M. S. C., Röösli, M., . . . Toledano, M. B. (2019). Night-time screen-based media device use and adolescents' sleep and healthrelated quality of life. *Environ Int, 124*, 66-78.

Moran, M. (2003). Arguments for rejecting the sequential Bonferroni in ecological studies. *Oikos, 100*(2), 403-405.

Murdock, K. K., Horissian, M., & Crichlow-Ball, C. (2016). Behav Sleep Med. *15, 3*(228-241).

Nursalam, N., Octavia, M., Tristiana, R. D., & Efendi, F. (2019). Association between insomnia and social network site use in Indonesian adolescents. *Nurs Forum, 54*, 149-156.

Pew Research Center. (2015). Mobile technology fact sheet. Retrieved Sep 4, 2015, from http://www.pewinternet.org/fact-sheets/mobile-technology-fact-sheet/

Pfitzner, R., Gorzelniak, L., Heinrich, J., Von Berg, A., Klumper, C., Bauer, C. P., . . . GINIPlus Study Group. (2013). Physical activity in German adolescents measured by accelerometry and activity diary: Introducing a comprehensive approach for data management and preliminary results. *PLoS One, 8*(6), e65192.

Przybylski, A. K. (2019). Digital screen time and pediatric sleep: Evidence from a preregistered cohort study. *J Pediatr, 205*, 218-223.

Punamaki, R.-L., Wallenius, M., Nygard, C.-H., Saarni, L., & Rimpela, A. (2007). Use of information and communication technology (ICT) and perceived health in adolescence: The role of sleeping habits and waking-time tiredness. *J Adolescence, 30*(4), 569-585.

Ryde, G. C., Gilson, N. D., Suppini, A., & Brown, W. J. (2012). Validation of a novel, objective measure of occupational sitting. *J Occup Health, 54*, 383-386.

Sadeh, A., Sharkey, K. M., & Carskadon, M. A. (1994). Activity-based sleep-wake identification: An empirical test of methodological issues. *Sleep, 17*(3), 201-207.

Shye, A., Scholbrock, B., Memik, G., & Dinda, P. A. (2010). *Characterizing and modeling user activity on smartphones: Summary.* Paper presented at the SIGMETRICS'10, New York, USA.

Soikkeli, T., Karikoski, J., & Hammainen, H. (2011). *Diversity and end user context in smartphone usage sessions.* Paper presented at the Fifth International Conference on Next Generation Mobile Applications and Services.

Statistista. (2015). Number of smartphone users worldwide from 2014 to 2020 (in billions) Retrieved Apr 30, 2019, from http://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

Toon, E., Davey, M. J., Hollis, S. L., Nixon, G. M., Horne, R. S. C., & Biggs, S. N. (2016). Comparison of commercial wrist-based and smartphone accelerometers, actigraphy, and PSG in a clinical cohort of children and adolescents. *J Clin Sleep Med, 12*(3), 343-350.

Twenge, J. M., Hisler, G. C., & Krizan, Z. (2019). Associations between screen time and sleep duration are primarily driven by portable electronic devices: evidence from a population-based study of U.S. children ages 0-17. *Sleep Med*(article in press).

Vanhelst, J., Béghin, L., Drumez, E., Coopman, S., & Gottrand, F. (2017). Awareness of wearing an accelerometer does not affect physical activity in youth. *BMC Med Res Methodol, 17*, 99.

Wang, P. Y., Chen, K. L., Yang, S. Y., & Lin, P. H. (2019). Relationship of sleep quality, smartphone dependence, and health-related behaviors in female junior college students. *PLoS One, 14*(4), e0214769.

Wong, F. Y. (2017). Influence of Pokémon Go on physical activity levels of university players: A cross-sectional study. *Int J Health Geogr, 16*, 8.

Wood, B., Rea, M. S., Plitnick, B., & Figueiro, M. G. (2013). Light level and duration of exposure determine the impact of self-luminous tablets on melatonin suppression. *Appl Ergon, 44*(2), 237-240.

Woods, H. C., & Scott, H. (2016). #Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. *J Adolescence, 51*, 41-49.

Yland, J., Guan, S., Emanuele, E., & Hale, L. (2015). Interactive vs passive screen time and nighttime sleep duration among school-aged children. *Sleep Health, 1*, 191-196.

Title: Temporal association between objectively-measured smartphone usage, sleep quality, and physical activity among Chinese adolescents and young adults

Running title: Smartphone, sleep, and physical activity

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ABSTRACT

We studied the association between objectively-measured smartphone usage and objectively-measured sleep quality and physical activity for seven consecutive days among Hong Kong adolescents and young adults aged 11-25 (n=357, 67% female). We installed an app that tracked the subjects' smartphone usage and had them wear an ActiGraph GT3X accelerometer on their wrist to measure their sleep quality and physical activity level. Smartphone usage data were successfully obtained from 187 participants (52.4%). The participants on average spent 2 hours 46 minutes per day on their smartphone. Multilevel regression showed that one minute of daytime smartphone usage was associated with 0.07 minute decrease in total sleeping time that night (p=0.043, 95% CI: -0.14, -0.003). Broken down for different usage purposes, one minute of daytime social network usage and games and comics was associated with a 0.28 (p=0.02, 95% CI: -0.52, -0.04) minute and 0.18 minute (p=0.01, 95% CI: -0.32, -0.04) decrease in total sleeping time that night, respectively. One minute of daytime smartphone usage was associated with 4.55 steps increase in the number of steps (p=0.001, 95% CI: 1.77, 7.34) on the next day. To conclude, time spent on smartphone at daytime was associated with total sleeping time that night and number of steps next day, but was not associated with sleep efficiency, wake after sleep onset, and MVPA among Hong Kong adolescents and young adults.

Keywords: exercise; gaming; screen; smart device; smartphone monitoring; youth

1. INTRODUCTION

The use of smartphones has been increasing rapidly in recent years. The number of smartphone users worldwide was 1.5 billion in 2014 and this figure is expected to be doubled in 2020 (Statistista, 2015). Smartphones have substituted for mp3 music players, video players, and handheld game consoles, as they allow easy access to all of these functions at any time and any place at the user's convenience (Kwon, Kim, Cho, & Yang, 2013). Smartphones also allow for the taking of instant photos and videos and the sharing of them through the internet. Moreover, smartphones allow users to download attractive and powerful applications for education, entertainment, and stock transactions. Smartphones are becoming so important that 29% of their owners "can't imagine living without" them (Pew Research Center, 2015).

Smartphone ownership and usage are a global phenomenon, with Hong Kong being one of the cities with the highest penetration rates around the world (ranked 8th out of 47 countries or places in 2013 (Mashable, 2013)). Local studies have revealed that almost all adults, more than 50% of primary school students, and more than 90% of secondary school students possess at least one smartphone (HKSARG Department of Health, 2015). Another study conducted by the Hong Kong Polytechnic University showed that 30% of school students used smart devices (including smartphones and tablets) for one to four hours per day (Hong Kong Polytechnic University Department of Physiotherapy, 2013).

While appropriately using smartphones can improve our quality of life, excessive usage can possibly lead to adverse health outcomes. The excessive usage of smartphones was associated with sedentary lifestyles (Lepp, Barkley, Sanders, Rebold, & Gates, 2013), poor sleeping habits (Punamaki, Wallenius, Nygard, Saarni, & Rimpela, 2007), and increased waking-time tiredness (Punamaki et al., 2007). A recent large-scale cross-sectional study among adolescents in Norway showed that both the daytime and bedtime use of electronic devices was associated with sleep problems (Hysing et al., 2015), confirming the theoretical pathway that the lighted screen of smartphone suppresses melatonin and affects sleep. Furthermore, increased time spent in bedtime smartphone usage will shorten the user's total sleeping time, and the resulted tiredness may reduce time spent in physical activity the next day.

Note that all of the aforementioned studies suffered a common major limitation, namely the cross-sectional nature that the possibility of reverse causation (that is, sleep quality causing smartphone usage) could not be eliminated, the use of the self-report level of smartphone usage, in which the reporting was subjected to recall bias (Hysing et al., 2015), unknown validity and reliability (Hysing et al., 2015), and an inability to track the frequently-changing smartphone usage habit (Benson et al., 2013).

Objectively-measured data on smartphone usage can be obtained by directly monitoring smartphone activities. Many smartphone monitoring applications have been written, most of which have been aimed at collecting usage information on data transfer and battery power consumption for further hardware development and improvement (Bohmer, Hecht, Schoning, Kruger, & Bauer, 2011; Do, Blom, & Gatica-Perez, 2011; Falaki, Mahajan, & Estrin, 2011; Falaki et al., 2010; Shye, Scholbrock, Memik, & Dinda, 2010; Soikkeli, Karikoski, & Hammainen, 2011). Very few studies have correlated objectively-measured smartphone usage with other outcomes; to the best of our knowledge, there exists only one study correlating objectively-measured smartphone usage with personality traits (Chittaranjan, Blom, & Gatica-Perez, 2013). To date, there have been no studies on the association between objectively-measured smartphone usage and health outcomes. Here, we studied the temporal association between objectively-measured smartphone usage in a day, the accelerometer-measured sleep quality that night, and the accelerometer-measured physical activity the next day measured for seven consecutive days in Hong Kong Chinese adolescents and young adults. Furthermore, to complete the examination of the possible bidirectional association between smartphone usage and sleep quality, we also studied the temporal association between the accelerometer-measured sleep quality in a night and the objectively-measured daytime smartphone usage in the next day.

2.METHODS

2.1.Participants

This study was conducted from March 2017 to May 2018. The participants were recruited from one secondary school (Tai Po Sam Yuk Secondary School, which corresponds to Years 7 to 12 in the US education system) and two universities (Hong Kong Polytechnic University and Education University of Hong Kong) in Hong Kong. In the secondary school, invitation letters were sent to the parents of all students. In the two universities, invitation emails were sent to all undergraduate students. Only those aged 11-25, who were able to speak and read Chinese, and owned a smartphone with the Android operating system were recruited to take part in this study. Phones with the Apple iOS operating system were excluded because Apple iOS app programmers are not allowed to collect smartphone usage data continuously. Written consent was obtained from all of the participants. For participants under the age of 18, parental written consent was also obtained. As a token of appreciation, a supermarket cash coupon worth HK $100 (approximately US $13) was given to the participants after the data were collected. This study was approved by the Human Subjects Ethics Sub-Committee of the Hong Kong Polytechnic University.

2.2.Data collection

2.2.1.Objectively-measured smartphone usage. We installed a smartphone usage tracking app (created by our team) on the smartphone of all of the participants' smartphone for seven consecutive days. This app tracked the opening and closing of all apps in the smartphone. No private or personal data, such as the contents of instant messages and the web pages that were browsed, were collected. For those participants who possessed more than one smartphone, we installed the app in their most commonly-used phone. We defined an app as being used when it was running in the graphical interface. It should be noted that the opening of one app would trigger the closure of the app currently being used, if any. The usage time was tracked by seconds. The names of the apps being used, their opening time, and closing time were stored in the smartphone and uploaded to a remote server (Firebase) once internet connection was available, and all uploaded data were removed from the smartphone.

2.2.2.Sleep quality and physical activity level. During the seven-day monitoring period, all of the participants concurrently wore an ActiGraph GT3X accelerometer. This is a wrist-worn, water-proof accelerometer that has been validated for measuring sitting time (Ryde, Gilson, Suppini, & Brown, 2012), physical activity (Pfitzner et al., 2013). and sleeping time.(P. H. Lee & Suen, 2017; Toon et al., 2016) The participants were instructed to wear the accelerometer on their non-dominant hand for 24 hours a day over seven consecutive days. They were asked to record the removal time in a logbook, if any (for example, when accelerometer might become damaged). Data were collected in 1-minute epoch. To synchronize the accelerometer data with smartphone usage data, when initializing the accelerometers Greenwich Mean Time +8, obtained via the internet, were used.

2.3.Data processing

2.3.1.Sleep quality and physical activity level. Peak acceleration in the three axes was extracted from the raw acceleration. The resultant acceleration of the raw acceleration from three axes was summarized by counts per minute (CPM). CPM of $\geq$4,514 of the vector magnitude was classified as moderate-to-vigorous-intensity activity (MVPA) (calibrated among Hong Kong young adults (P. H. Lee & Tse, 2019)). Non-wearing time was defined as consecutive zero counts for 60 or more minutes. The amount of wearing time in a day was computed by subtracting the non-wearing time and sleeping time (determined by the accelerometer) from 24 hours. A valid day must include at least 10 hours of wearing time excluding sleeping time. Steps were detected using the built-in algorithm of the ActiGraph that based on the acceleration amplitude and frequency (John, Morton, Arguello, Lyden, & Bassett, 2018). Steps accumulated in time length of <10 seconds were removed by the ActiGraph. As we used a temporal analysis that treated a day as the unit of analysis and did not require the averaging of PA and sleep parameters of individual participants throughout the whole study period, participants who provided at least one valid day could be included in the analysis.

All of the minutes recorded from the accelerometers were classified as either sleep or awake using Sadeh's algorithm (Sadeh, Sharkey, & Carskadon, 1994). According to Sadeh's algorithm, the sleep index of a minute is defined as 7.601 – (0.065×AVG) – (1.08×NATS) – (0.056×SD) – (0.703×LG), where AVG is the average CPM of the 11 minutes centered at the current minute, NATS is the number of minute with CPM between 50 to 99 at the 11-min period, SD is the standard deviation of the current and five preceding minutes, and LG is the natural log of the CPM+1 (to avoid log of 0) at the current minute. Recorded minutes with sleep index of ≥-4 will be classified as sleep, and awake otherwise. Sleep onset was defined as the first 15 minutes of consecutive sleeping minutes, and awakening time was defined as the first 15 minutes of consecutive wake minutes. The total sleeping period was measured as beginning at sleep onset and ending at awakening. Total sleeping time was defined as the sleeping time within the total sleeping period. Sleep efficiency was defined as the total sleeping time divided by the total sleeping period. Wake after sleep onset (WASO) was defined as the waking time within the total sleeping period.

2.3.2Objectively-measured smartphone usage. All recorded smartphone applications were categorized under social network (Facebook, Twitter, Instagram, Weibo, etc.), instant messaging (Whatsapp, Skype, Line, Wechat, etc.), web browsing (including browser and apps developed for browsing specific websites), games and comics (except games plug-ins and guides), multimedia (related to music, video, and image/photo, for example YouTube and MOOV), camera (including beauty-themed photo and video apps such as Meitu), and health (pedometer, GPS distance and speed tracker, etc.). The time spent on each usage session was computed as the difference between the closing time and opening time. Usage sessions of less than 1 second were discarded as such short times were likely to be an indication that the app had been accidentally pressed. All smartphone usage time were classified as either occurring in the daytime (defined as the time from waking up to 1 hour before sleep, where the sleeping time was identified using the accelerometer data), bedtime (defined as 1 hour before sleep), or during wakeful moment at sleep (or WASO).

2.4.Statistical analysis

Descriptive statistics (mean, SD, frequency) were used to summarize the pattern of smartphone usage, sleep quality, and physical activity level. Multilevel regression was used to examine the temporal association between daytime and bedtime smartphone usage with sleep quality that night and physical activity on the following day, adjusted for the data source (secondary school / university), sex, and within-subject correlation. The within-subject correlation was assumed to have an auto-regressive structure of order one (or AR(1)). The same model was also used to examine the temporal association between the sleep quality and the daytime smartphone usage on the following day. The intra-class correlation (ICC), auto-correlation, and R^2 of all models were reported. The data from the first day that the smartphone usage tracking app was installed and the accelerometer was distributed were excluded due to the incompleteness of the data. All data were analyzed both among the overall sample and stratified by school type (secondary school versus university). Histograms of the residuals and residual plots were used to examine the assumptions of multilevel regression, including normality, homoscedasticity, and independence of observations. A *p*-value of <0.05 was considered significant, and multiple comparisons were not controlled because of the high number of correlated null hypotheses in this study (Moran, 2003).

3.RESULTS

A total of 393 students (156 from the secondary school and 237 from the two universities) agreed to participate, and 357 of them who provided at least one valid day of accelerometer data were included in the current analysis. Table 1 shows the characteristics of the participants. Nearly two-thirds of them were university students. The secondary school sample was balanced in gender, but in the university sample less than one-fourth of them were male. The sleep quality and physical activity level of the two samples were comparable.

[Table 1 inserted here]

Of the 357 participants, smartphone usage data were successfully tracked for 187 (52.4%). The smartphone tracking app was written for Android 7.0 or above, and the tracking app did not work with some smartphones installed with earlier Android versions. The daytime and bedtime smartphone usage data are summarized in Table 2. The participants spent nearly 3 hours per day on their smartphone. Secondary school students on average spent 40 more minutes per day on smartphones than university students. The most common type of usage among secondary school students and university students were games and comics apps (1 hour 30 minutes per day) and instant messaging apps (1 hour 13 minutes per day), respectively. Bedtime smartphone usage was recorded in 464 (42.0%) out of the 1,106 measured nights. On average the participants spent 10 minutes per day on their smartphone during bedtime. Smartphone usage during WASO was recorded in 563 (50.9%) out of the 1,106 measured nights. On average the participants spent 29 minutes per day on their smartphone during WASO.

[Table 2 inserted here]

Table 3 shows the multilevel regression results of smartphone usage on sleep quality. Results among the overall sample showed that one minute of daytime smartphone usage was associated with 0.07 minute decrease in total sleeping time that night (*p*=0.043, 95% CI: -0.14, -0.003). Broken down for different usage purposes, one minute of daytime social network usage and games and comics was associated with a 0.28 (*p*=0.02, 95% CI: -0.52, -0.04) minute and 0.18 minute (*p*=0.01, 95% CI: -0.32, -0.04) decrease in total sleeping time that night, respectively. Daytime smartphone usage was not associated with sleep efficiency and WASO. One minute of bedtime social network usage was associated with 2.58 minute increase in total sleeping time that night (*p*=0.01, 95% CI: 0.60, 4.36). One minute of web browsing during WASO was associated with 2.29 minute increase in total sleeping time (*p*=0.047, 95% CI: 0.03, 4.55) and 0.46 minute of WASO (*p*=0.02, 95% CI: 0.08, 0.83) that night. Among secondary school students, one minute of daytime smartphone usage was associated with 0.12 minute decrease in total sleeping time that night (*p*=0.042, 95% CI: -0.23, -0.007). Broken down for different usage purposes, only social network (β=-0.39, *p*=0.03, 95% CI: -0.73, -0.04) was associated with total sleeping time. One minute of bedtime smartphone usage was associated with 0.32 minute increase in wake after sleep onset that night (*p*=0.04, 95% CI: 0.02, 0.62). One minute of smartphone usage during WASO was associated with sleep efficiency (β=0.013%, p=0.01, 95% CI: 0.003%, 0.023%) and WASO (β=-0.05, p=0.04, 95% CI: -0.10, -0.005). Among university students, smartphone usage during daytime, bedtime, and sleep were insignificantly associated with sleep quality. Broken down for different usage purposes, daytime tools usage (β=0.32, p=0.02, 95% CI: 0.04, 0.60) and bedtime social network usage (β=2.38, p=0.02, 95% CI: 0.37, 4.39) was associated with total sleeping time, while instant messaging (β=0.04, p=0.048, 95% CI: 0.001, 0.07), web browsing (β=0.47, p=0.02, 95% CI: 0.09, 0.84), and camera usage (β=25.79, p=0.01, 95% CI: 6.22, 45.36) during WASO were associated with WASO.

[Table 3 inserted here]

Table 4 shows the multilevel regression results of smartphone usage on physical activity level. One minute of daytime smartphone usage was associated with 7.15 steps increase in the number of steps (p=0.02, 95% CI: 1.02, 13.28) among secondary school students, 3.52 steps increase in the number of steps (p=0.03, 95% CI: 0.37, 6.66) among university students, and 4.55 steps increase in the number of steps (p=0.001, 95% CI: 1.77, 7.34) in the overall sample on the next day. Social network, instant messaging, tools, multimedia usage, and total smartphone usage (β=0.06, p=0.01, 95% CI: 0.01, 0.11) were positively associated with both the number of steps and the time spent on MVPA in the overall sample. Smartphone usage during bedtime and sleep were insignificantly associated with physical activity level, except web browsing during WASO was associated with number of steps (β=1153.07, p=0.04, 95% CI: 57.92, 2248.22) among secondary school students.

[Table 4 inserted here]

Table 5 shows that, for both secondary school students and university students, better sleep quality was associated with higher volume of physical activity level on the next day, except that one percent increase in sleep efficiency was associated with 112.44 step decrease (*p*=0.02, 95% CI: 12.55, 212.33) among secondary school students. Table 6 shows that all associations between sleep quality and daytime smartphone usage were insignificant except one percent increase in sleep efficiency was associated with 9.42 second decrease in time spent on web browsing the next day (*p*=0.02, 95% CI: -17.50, -1.33) among university students.

[Table 5 inserted here]

[Table 6 inserted here]

Histograms of the residuals and residual plots of all regressions are shown in Supplementary Figures S1 to S72. Overall speaking, the residuals were normal (except for sleep efficiency that was slightly skewed to the left), homoscedastic, and independent of each other.

The ICC, auto-correlation, and R2 of all multilevel regression models could be found in Supplementary Tables S1 to S4. The overall sample showed a small ICCs of 0.10-0.12 on total sleeping time and 0.14-0.15 on the number of steps, while the ICCs were of moderate size for ICC of sleep efficiency (0.27-0.28), WASO (0.26-0.27), and MVPA (0.30-0.31). The auto-correlation showed that the sleeping variables were only slightly auto-correlated among both secondary school students and university students, while the physical activity variables had a small-to-moderate auto-correlation. The difference between ICC and R^2 of the models showed that the independent variables (data source, gender, and smartphone usage) explained 7-10% on total sleeping time and 9-12% on sleep efficiency WASO, number of steps, and time spent on MVPA. In sum, the within-subject effect explained a larger proportion of variance than the between-subject effect for all sleep and PA variables.

4.DISCUSSION

We conducted a study to examine the association between objectively-measured smartphone usage, sleep quality, and physical activity level among Hong Kong Chinese adolescents and young adults. We found that the explanatory power of total smartphone usage on sleep quality among secondary school students, university students, and overall sample was 3.14%-5.89%, 0.16%-0.34%, and 0.02%-0.52%, respectively (Supplementary Table S5). We concluded that the explanatory power of smartphone usage on sleep among university students was negligible (with similar explanatory power among US children (Przybylski, 2019)), while smartphone usage was a significant contributor of sleep, in particular total sleeping time, among secondary school students. There were several advantages to using the objective measurement of smartphone usage. First, we could identify different purposes for which smartphone was being used, and showed the effect of smartphone use on different aspects of life. For instance, we found that only the use of social network apps and games and comics apps was associated with total sleeping time. Second, together with sleeping parameters objectively measured with accelerometer, we could define sleeping time and bedtime smartphone usage objectively, and exclude the possibility of reverse causation that sleep quality has a negligible effect on smartphone usage the next day. Note that our data did not rule out (and could not identify) the complex, bidirectional nature between sleep pattern and smartphone usage during sleep, whereby people with sleep problems would use their smartphone during bedtime as a way of spending their energy (Przybylski, 2019), and in turn the blue light emission from smartphone will suppress melatonin secretion that further delay sleep onset (Figueiro & Overington, 2016). Third, while the validity of self-reported smartphone usage was questionable, the source of measurement error could be eliminated through objective measurement of smartphone usage.

In studies on the association between smartphone usage and sleep quality, most used a self-reported questionnaire to measure sleep quality and only three studies measured sleep quality with a wrist-worn accelerometer (Cabré-Riera et al., 2019; Fobian, Avis, & Schwebel, 2016; Murdock, Horissian, & Crichlow-Ball, 2016). Surprisingly, all three studies found no association. On the one hand, the finding of a null association might be a true finding; on the other hand, it is possible that these studies committed a type II error because the sample sizes ranged from 55 to 110 only. Furthermore, in these studies, smartphone usage data were not collected in a daily manner and only the averaged accelerometer-measured sleep quality across the measurement period could be used, so that the within-subject variation was ignored. With a repeated measure of 814 nights in a study involving 187 subjects that both within-subject and between-subject variation could be examined, ours has the largest in sample size and showed that both daytime and bedtime smartphone usage were associated with total sleeping time but not with sleep efficiency and WASO.

Several researchers attempted to differentiate between the physiological effects of daytime and bedtime smartphone usage. Compared to other devices with electronic screens such as televisions and video game consoles, the smartphone is more commonly used in bed as they are portable and are usually placed very close to the user (Twenge, Hisler, & Krizan, 2019; Wood, Rea, Plitnick, & Figueiro, 2013). To the best of our knowledge, all existing studies have relied on self-reported data to determine bedtime smartphone usage. As the validity of self-reports of bedtime smartphone usage requires the accurate recalling of both bedtime and smartphone usage, we questioned the validity of self-report and used objective measure of sleep onset and smartphone usage to determine bedtime smartphone usage. The invalidity of self-reported bedtime smartphone usage is shown by the disagreement of our results with other existing self-reported results; for example a Taiwanese study using self-reported data showed that bedtime smartphone usage was very common (95%) among junior college students (Wang, Chen, Yang, & Lin, 2019), but the current study recorded such usage in less than half of the nights (42.4%). Our results also highlighted the importance of distinguishing between daytime and bedtime smartphone usage, as total sleeping time was negatively related to daytime usage but not related to bedtime usage. We found no association between smartphone usage, both daytime and bedtime, and sleeping efficiency, and these results did not agree with some previous findings (Amra et al., 2017; Carter, Rees, Hale, Bhattacharjee, & Paradkar, 2016; Lemola, Perkinson-Gloor, Brand, Dewald-Kaufmann, & Grob, 2015; Mireku et al., 2019). We believe that the effects of smartphone usage and sleep outcomes are still controversial (some other studies found a null association (Demirci, Akgönül, & Akpinar, 2015)) and warrant further investigations, especially through employing well-designed controlled trials. We suspect that, in previous studies, participants might mixed up bedtime smartphone usage and usage during WASO, as we found that smartphone usage during WASO did improve sleep efficiency. To the best of our knowledge, very few randomized controlled trials have been conducted in this direction, and some found a null association between smartphone usage and sleep outcomes due to small sample size (Dunican et al., 2017).

Besides the time of use, the purpose for which a smartphone is used may also have an impact on sleep outcomes. This study found that only using a smartphone for social network apps and games and comics apps, but not for other types of apps, was associated with total sleeping time. It was hypothesized that interactive smartphone use should have stronger effects on sleep than the passive viewing of a smartphone screen (Dworak, Schierl, Bruns, & Struder, 2007). Our results only partially agreed with this hypothesis. Social network app usage can be regarded as passive viewing as its use does not involve frequent touching of the phone. However, the contents of social network are updated extremely quickly and new updates can be expected to occur every minute. Therefore, users may be anxious about missing out on new content, and such anxiety may cause users to stay awake during the night (Woods & Scott, 2016). Yet, some studies found that social network use was, in fact, positively related to sleep quality (Nursalam, Octavia, Tristiana, & Efendi, 2019), partially because social network sites can help users to connect, make new friends, and share their stress (Nursalam et al., 2019). In addition to social network apps, instant messaging apps were also commonly used among our subjects, and we found no association between its use and all sleep outcomes. It was hypothesized that it is difficult to leave a discussion initiated through instant messaging, which thereby delays sleep onset. This hypothesis was supported by the fact that texting was negatively associated with sleep quality (Exelmans & Van den Bulck, 2016) and its effect on sleep duration was the strongest among other electronic screen usages (Yland, Guan, Emanuele, & Hale, 2015). However, we questioned the validity of these results as they relied on self-reported time spent on instant messaging and such data, being recalled data, is inherently unreliable. Our data showed that instant messaging apps were used frequently, at an average of 363.7 times per day and that each session only lasted for an average of 26 seconds. We believe that the frequent and short usage nature of instant messaging apps made the recalling of time spent on them challenging.

It was generally expected that the use of a smartphone would lead to a sedentary and inactive lifestyle due to its sedentary nature (Kenney & Gortmaker, 2017; Lepp et al., 2013). Surprisingly, our data showed that social network, instant messaging, tools, and multimedia app usage at daytime were all positively associated with physical activity level. We believe that there was a bi-directional causation. Those who were more physically active might have spent more time on social network and instant messaging apps to share their photos and information. Similarly, some of the multimedia app usage might have been occurred concurrently with physical activity (e.g., playing a video during jogging on a treadmill). On the other hand, our data found no association between games and health app usage and physical activity level. Recently, some augmented reality games developed for smartphone have encouraged walking in the real world (e.g., Pokémon GO), and there is evidence to show that their use is promoting engagement in physical activity (Howe et al., 2016; Wong, 2017). In the current study, too few subjects played Pokémon GO (11 out of 187, 5.9%); therefore, the health-promoting effect of this kind of augmented reality game might have been diluted by the sedentary effect of other kinds of games. Similarly, users of health-related apps, for instance pedometer apps, were found to be physically more active than non-users (Carroll et al., 2017; Ernsting et al., 2017). In the current study, too few subjects used health-related apps (31 out of 187, 16.6%); less than the previously reported percentage (34.1%) in a US sample (Carroll et al., 2017). Most importantly, no secondary school students in our sample used any kind of health-related apps during the measurement period, therefore, we were unable to detect the associations between the usage of health-related apps, sleep quality, and physical activity level.

The major limitation of this study lied in the area of sampling and data collection. Only Android users were recruited in this study and cautions should be taken when our results are generalized to users of other smartphones. This also explains the small number of adolescent participants in our sample; most of the students in our recruited secondary schools were using an iPhone that is not supported by our tracking app. Nonetheless, our sample has comparable smartphone usage level (206 min/day) with Korean college students (210 min/day) (U. Lee et al., 2014) and US adults (159 min/day) (Deng et al., 2019). In our sample, about 10% of the participants owned more than one smartphone. Since the smartphone usage tracking app was only installed in one smartphone of the subjects, we might have underestimated the total smartphone usage. Another limitation was that our smartphone tracking app could not record the usage of some Android default system apps, for example Google Chrome, the default web browser of Android system, in some versions of Android operating system. It only affected the measurement of time spent on web browsing but not on the other usage types. A minor limitation was that different recruitment approach was used in secondary school and universities that might affect the generalizability of our results. It is known that monitoring of PA level with accelerometers could lead to an increase in PA among older adults (Cooper et al., 2018), but the monitoring has no impact among adolescents (Vanhelst, Béghin, Drumez, Coopman, & Gottrand, 2017). To the best of our knowledge, we were unable to identify any studies that examine the impact of wearing an accelerometer on sleep quality among adolescents, therefore we could not determine its impact in our sample. Smartphone usage time during WASO was subjected to error as the phone usage may not be performed by the smartphone owner, or the actual waking time was misclassified as sleep by the ActiGraph (Kushida et al., 2001).

5.CONCLUSIONS

Time spent on social network apps and games and comics apps at daytime, social network apps at bedtime, and web browsing apps during WASO was associated with total sleeping time. Time spent on social network apps, instant messaging apps, and multimedia apps at daytime were associated with the number of steps and MVPA among Hong Kong Chinese adolescents and young adults. All other types of smartphone usage were not associated with sleep quality and physical activity. The study design could not infer causality and further investigations on these effects employing experimental designs are warranted.

Availability of data and materials

The dataset(s) supporting the conclusions of this article is(are) available upon request.

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Competing interests

The authors declare that there are no known conflicts of interest associated with this publication.

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REFERENCES

Amra, B., Shahsavari, A., Shayan-Moghadam, R., Mirheli, O., Moradi-Khaniabadi, B., Bazukar, M., . . . Kelishadi, R. (2017). The association of sleep and late-night cell phone use among adolescents. *J Pediatr (Rio J), 93*(6), 560-567.

Benson, V. S., Pirie, K., Schuz, J., Reeves, G. K., Beral, V., Green, J., & for the Million Women Study Collaborators. (2013). Mobile phone use and risk of brain neoplasms and other cancers: prospective study. *Int J Epidemiol, 42*(3), 792-802.

Bohmer, M., Hecht, B., Schoning, J., Kruger, A., & Bauer, G. (2011). *Falling asleep with Angry Birds, Facebook and Kindle - A large scale study on mobile application usage.* Paper presented at the MobileHCI 2011, Stockholm, Sweden.

Cabré-Riera, A., Torrent, M., Donaire-Gonzalez, D., Vrijheid, M., Cardis, E., & Guxens, M. (2019). Telecommunication devices use, screen time and sleep in adolescents. *Environ Res, 171*, 341-347.

Carroll, J. K., Moorhead, A., Bond, R., LeBlanc, W. G., Petrella, R. J., & Fiscella, K. (2017). Who uses mobile phone health apps and does use matter? A secondary data analytics approach. *J Med Internet Res, 19*(4), e125.

Carter, B., Rees, P., Hale, L., Bhattacharjee, D., & Paradkar, M. (2016). Association between portable screen-based media device access or use and sleep outcomes: A systematic review and meta-analysis. *JAMA Pediatr, 170*(12), 1202-1208.

Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2013). Mining large-scale smartphone data for personality studies. *Pers Ubiquit Comput, 17*(3), 433-450.

Cooper, C., Gross, A., Brinkman, C., Pope, R., Allen, K., Hastings, S., . . . Goode, A. P. (2018). The impact of wearable motion sensing technology on physical activity in older adults. *Exp Gerontol, 112*, 9-19.

Demirci, K., Akgönül, M., & Akpinar, A. (2015). Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students. *4, 2*(85-92).

Deng, T., Kanthawala, S., Meng, J., Peng, W., Kononova, A., Hao, Q., . . . David, P. (2019). Measuring smartphone usage and task switching with log tracking and self-reports. *Mobile Media Commun, 7*(1), 3-23.

Do, T. M. T., Blom, J., & Gatica-Perez, D. (2011). *Smartphone usage in the wild: a large-scale analysis of applications and context.* Paper presented at the ICMI'11, Alicante, Spain.

Dunican, I. C., Martin, D. T., Halson, S. L., Reale, R. J., Dawson, B. T., Caldwell, J. A., . . . Eastwood, P. R. (2017). The effects of the removal of electronic devices for 48 hours on sleep in elite judo athletes. *J Strength Cond Res, 31*(10), 2832-2839.

Dworak, M., Schierl, T., Bruns, T., & Struder, H. K. (2007). Impact of singular excessive computer game and television exposure on sleep patterns and memory performance of school-aged children. *Pediatrics, 120*(5), 978-985.

Ernsting, C., Dombrowski, S. U., Oedekoven, M., O'Sullivan, J. L., Kanzler, M., Kuhlmey, A., & Gellert, P. (2017). Using smartphones and health apps to change and manage health behaviors: A population-based survey. *J Med Internet Res, 19*(4), e101.

Exelmans, L., & Van den Bulck, J. (2016). Bedtime mobile phone use and sleep in adults. *Soc Sci Med, 148*, 93-101.

Falaki, H., Mahajan, R., & Estrin, D. (2011). *SystemSens: A tool for monitoring usage in smartphone research deployments.* Paper presented at the MobiArch'11, Bethesda, Maryland, USA.

Falaki, H., Mahajan, R., Kandula, S., Lymberopoulos, D., Govindan, R., & Estrin, D. (2010). *Diversity in smartphone usage.* Paper presented at the MobiSys'10, San Francisco, California, USA.

Figueiro, M., & Overington, D. (2016). Self-luminous devices and melatonin suppression in adolescents. *Lighting Res Technol, 48*, 966-975.

Fobian, A. D., Avis, K., & Schwebel, D. C. (2016). The impact of media use on adolescent sleep efficiency. *J Dev Behav Pediatr, 37*(1), 9-14.

HKSARG Department of Health. (2015). Health Effects on Use of Internet and Electronic Screen Products. Retrieved Sep 4, 2015, from http://www.studenthealth.gov.hk/english/internet/health_effects.html

Hong Kong Polytechnic University Department of Physiotherapy. (2013). A survey on health effects of the use of smart phones and related electronic products in Hong Kong [Press release]

Howe, K. B., Suharlim, C., Ueda, P., Howe, D., Kawachi, I., & Rimm, E. B. (2016). Gotta catch'em all! Pokémon GO and physical activity among young adults: difference in differences study. *BMJ, 355*, i6270.

Hysing, M., Pallesen, S., Stormark, K. M., Jakobsen, R., Lundervold, A. J., & Sivertsen, B. (2015). Sleep and use of electronic devices in adolescence: results from a large population-based study. *BMJ Open, 5*, e006748.

John, D., Morton, A., Arguello, D., Lyden, K., & Bassett, D. (2018). "What Is a Step?" Differences in How a Step Is Detected among Three Popular Activity Monitors That Have Impacted Physical Activity Research. *Sensors, 18*(4), 1206.

Kenney, E. L., & Gortmaker, S. L. (2017). United States adolescents' television, computer, videogame, smartphone, and tablet use: Associations with sugary drinks, sleep, physical activity, and obesity. *J Pediatr, 182*, 144-149.

Kushida, C., Chang, A., Gadkary, C., Guilleminault, C., Carrillo, O., & Dement, W. C. (2001). Comparison of actigraphic, polysomnographic, and subjective assessment of sleep parameters in sleep-disordered patients. *Sleep Med, 2*(5), 389-396.

Kwon, M., Kim, D. J., Cho, H., & Yang, S. (2013). The Smartphone Addiction Scale: Development and validation of a short version for adolescents. *PLoS One, 8*(12), e83558.

Lee, P. H., & Suen, L. K. P. (2017). The convergent validity of Actiwatch 2 and ActiGraph Link accelerometers in measuring total sleeping period, wake after sleep onset, and sleep efficiency in free-living condition. *Sleep Breath, 21*(1), 209-215.

Lee, P. H., & Tse, A. C. Y. (2019). Calibration of Wrist-worn ActiWatch 2 and ActiGraph wGT3X for Assessment of Physical Activity in Young Adults. *Gait Posture, 68*, 141-149.

Lee, U., Lee, J., Ko, M., Lee, C., Kim, Y., Yang, S., . . . Song, J. (2014). *Hooked on* *smartphones: an exploratory study on smartphone overuse among college students*. Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems New York.

Lemola, S., Perkinson-Gloor, N., Brand, S., Dewald-Kaufmann, J. F., & Grob, A. (2015). Adolescents' electronic media use at night, sleep disturbance, and depressive symptoms in the smartphone age. *J Youth Adolescence, 44*, 405-418.

Lepp, A., Barkley, J. E., Sanders, G. J., Rebold, M., & Gates, P. (2013). The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. *Int J Behav Nutr Phys Act, 10*, 79.

Mashable. (2013). The 15 Countries With the Highest Smartphone Penetration. Retrieved 9 May, 2019, from https://mashable.com/2013/08/27/global-smartphone-penetration/

Mireku, M. O., Barker, M. M., Mutz, J., Dumontheil, I., Thomas, M. S. C., Röösli, M., . . . Toledano, M. B. (2019). Night-time screen-based media device use and adolescents' sleep and healthrelated quality of life. *Environ Int, 124*, 66-78.

Moran, M. (2003). Arguments for rejecting the sequential Bonferroni in ecological studies. *Oikos, 100*(2), 403-405.

Murdock, K. K., Horissian, M., & Crichlow-Ball, C. (2016). Behav Sleep Med. *15, 3*(228-241).

Nursalam, N., Octavia, M., Tristiana, R. D., & Efendi, F. (2019). Association between insomnia and social network site use in Indonesian adolescents. *Nurs Forum, 54*, 149-156.

Pew Research Center. (2015). Mobile technology fact sheet. Retrieved Sep 4, 2015, from http://www.pewinternet.org/fact-sheets/mobile-technology-fact-sheet/

Pfitzner, R., Gorzelniak, L., Heinrich, J., Von Berg, A., Klumper, C., Bauer, C. P., . . . GINIPlus Study Group. (2013). Physical activity in German adolescents measured by accelerometry and activity diary: Introducing a comprehensive approach for data management and preliminary results. *PLoS One, 8*(6), e65192.

Przybylski, A. K. (2019). Digital screen time and pediatric sleep: Evidence from a preregistered cohort study. *J Pediatr, 205*, 218-223.

Punamaki, R.-L., Wallenius, M., Nygard, C.-H., Saarni, L., & Rimpela, A. (2007). Use of information and communication technology (ICT) and perceived health in adolescence: The role of sleeping habits and waking-time tiredness. *J Adolescence, 30*(4), 569-585.

Ryde, G. C., Gilson, N. D., Suppini, A., & Brown, W. J. (2012). Validation of a novel, objective measure of occupational sitting. *J Occup Health, 54*, 383-386.

Sadeh, A., Sharkey, K. M., & Carskadon, M. A. (1994). Activity-based sleep-wake identification: An empirical test of methodological issues. *Sleep, 17*(3), 201-207.

Shye, A., Scholbrock, B., Memik, G., & Dinda, P. A. (2010). *Characterizing and modeling user activity on smartphones: Summary.* Paper presented at the SIGMETRICS'10, New York, USA.

Soikkeli, T., Karikoski, J., & Hammainen, H. (2011). *Diversity and end user context in smartphone usage sessions.* Paper presented at the Fifth International Conference on Next Generation Mobile Applications and Services.

Statistista. (2015). Number of smartphone users worldwide from 2014 to 2020 (in billions) Retrieved Apr 30, 2019, from http://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

Toon, E., Davey, M. J., Hollis, S. L., Nixon, G. M., Horne, R. S. C., & Biggs, S. N. (2016). Comparison of commercial wrist-based and smartphone accelerometers, actigraphy, and PSG in a clinical cohort of children and adolescents. *J Clin Sleep Med, 12*(3), 343-350.

Twenge, J. M., Hisler, G. C., & Krizan, Z. (2019). Associations between screen time and sleep duration are primarily driven by portable electronic devices: evidence from a population-based study of U.S. children ages 0-17. *Sleep Med*(article in press).

Vanhelst, J., Béghin, L., Drumez, E., Coopman, S., & Gottrand, F. (2017). Awareness of wearing an accelerometer does not affect physical activity in youth. *BMC Med Res Methodol, 17*, 99.

Wang, P. Y., Chen, K. L., Yang, S. Y., & Lin, P. H. (2019). Relationship of sleep quality, smartphone dependence, and health-related behaviors in female junior college students. *PLoS One, 14*(4), e0214769.

Wong, F. Y. (2017). Influence of Pokémon Go on physical activity levels of university players: A cross-sectional study. *Int J Health Geogr, 16*, 8.

Wood, B., Rea, M. S., Plitnick, B., & Figueiro, M. G. (2013). Light level and duration of exposure determine the impact of self-luminous tablets on melatonin suppression. *Appl Ergon, 44*(2), 237-240.

Woods, H. C., & Scott, H. (2016). #Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. *J Adolescence, 51*, 41-49.

Yland, J., Guan, S., Emanuele, E., & Hale, L. (2015). Interactive vs passive screen time and nighttime sleep duration among school-aged children. *Sleep Health, 1*, 191-196.

Table 1. Demographic characteristics and accelerometer-measured sleep quality and physical activity level of the participants (n=357)

	Secondary school students (number of participants=125)	University students (number of participants=232)	Overall (number of participants=187)
Variable	Frequency (%)	Frequency (%)	Frequency (%)
Sex			
Male	62 (50.4%)	55 (23.7%)	117 (33.0%)
Female	61 (49.6%)	177 (76.3%)	238 (67.0%)
	Mean (SD)	Mean (SD)	Mean (SD)
Age	18.4 (3.3)	18.4 (3.3)	18.4 (3.3)
Sleep quality	Secondary school students (number of participants=32, number of days=176)	University students (number of participants=155, number of days=930)	Secondary school students (number of participants=187, number of days=1,106)
Total sleeping time (hr)	7.5 (1.8)	7.5 (1.8)	7.5 (1.8)
Sleep efficiency (%)	94.3 (4.5)	94.9 (4.1)	94.7 (4.2)
Wake after sleep onset (min)	25.2 (19.9)	22.6 (17.8)	23.4 (18.5)
Physical activity level	Secondary school students (number of participants=123, number of days=459)	University students (number of participants=229, number of days=1,058)	Secondary school students (number of participants=352, number of days=1,517)
Number of step	10,315 (4,950)	10,003 (4,186)	10,095 (4,423)
Moderate-to-vigorous physical activity (min)	162.7 (102.6)	137.2 (73.2)	144.6 (83.6)

Sleep and physical activity data were reported across measurement days.

Table 2. Smartphone usage (min) of the participants (number of participants=187, number of days=1,106)

	Secondary school students (number of participants=32, number of days=176)			University students (number of participants=155, number of days=930)			Overall (number of participants=187, number of days=1,106)		
Smartphone usage	Daytime (mean (SD))	Bedtime (mean (SD))	During ~~sleep~~WASO (mean (SD))	Daytime (mean (SD))	Bedtime (mean (SD))	During ~~sleep~~WASO (mean (SD))	Daytime (mean (SD))	Bedtime (mean (SD))	During ~~sleep~~WASO (mean (SD))
Social network	23.1 (101.9)	1.1 (7.0)	2.2 (13.8)	24.2 (52.1)	2.0 (8.8)	4.4 (26.8)	24.0 (62.7)	1.9 (3.8)	4.0 (25.2)
Instant messaging	54.8 (96.5)	3.3 (12.2)	9.6 (43.9)	73.4 (112.6)	3.9 (12.3)	11.5 (73.8)	70.5 (110.3)	3.8 (12.3)	11.2 (69.9)
Tools	16.1 (45.1)	1.6 (10.9)	16.5 (106.7)	25.4 (58.1)	1.7 (9.8)	7.9 (65.5)	23.9 (56.3)	1.7 (10.0)	9.3 (73.6)
Web browsing	2.7 (13.8)	0.4 (2.4)	0.2 (1.3)	4.1 (17.5)	0.5 (3.3)	0.8 (6.1)	3.9 (17.0)	0.4 (3.2)	0.7 (5.6)
Games and comics	89.8 (199.1)	4.5 (13.0)	7.3 (28.3)	24.2 (78.1)	1.1 (6.7)	2.0 (23.2)	34.7 (109.5)	1.7 (8.1)	2.9 (24.1)
Multimedia	20.3 (60.7)	1.1 (7.0)	3.7 (46.3)	6.7 (32.0)	0.9 (6.5)	0.6 (7.6)	8.8 (38.3)	0.9 (6.6)	1.1 (19.7)
Health	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)	0.4 (3.0)	0.0 (0.5)	0.0 (0.5)	0.3 (2.7)	0.0 (0.5)	0.0 (0.5)
Camera	0.6 (4.0)	0.0 (0.1)	0.0 (0.1)	0.2 (2.5)	0.0 (0.1)	0.0 (0.1)	0.3 (2.8)	0.0 (0.1)	0.0 (0.1)
Total	207.4 (309.1)	12.1 (26.4)	39.4 (136.6)	158.6 (199.4)	10.1 (21.3)	27.3 (107.6)	166.4 (221.0)	10.4 (22.2)	29.2 (112.7)

Daytime was defined as the time from waking up to 1 hour before sleep, and bedtime was defined as 1 hour before sleep. Sleep onset was defined as the first 15 minutes of consecutive sleeping minutes. WASO: wake after sleep onset

Table 3. Multilevel regression results (reported as coefficient (95% confidence interval)) of smartphone usage (min) on sleep quality (number of participants=187, number of days=814)

	Secondary school students (number of participants=32, number of days=109)			University students (number of participants=155, number of days=705)			Overall (number of participants=187, number of days=814)		
	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (%)
Daytime									
Social network	-0.39* (-0.73, -0.04); β=-0.003	-0.0088 (-0.0090, 0.0267); β=0.002	-0.04 (-0.12, 0.04); β=-0.002	-0.19 (-0.51, 0.14); β=-0.002	-0.0034 (-0.0166, 0.0098); β=-0.08	0.004 (-0.06, 0.05); β=-0.0001	-0.28* (-0.52, -0.04); β=-0.003	-0.0013 (-0.0116, 0.0090); β=-0.0003	0.02 (-0.07, 0.12); β=-0.0007
Instant messaging	0.14 (-0.22, 0.49); β=0.001	-0.0019 (-0.0175, 0.0138); β=-0.0004	0.04 (-0.04, 0.11); β=0.002	-0.08 (-0.22, 0.06); β=-0.001	-0.0022 (-0.0080, 0.0036); β=-0.05	0.01 (-0.02, 0.03); β=0.0005	-0.06 (-0.19, 0.07); β=-0.0006	-0.0030 (-0.0084, 0.0025); β=-0.0007	0.02 (-0.03, 0.06); β=0.001
Tools	-0.46 (-1.15, 0.23); β=-0.004	-0.0006 (-0.0275, 0.0263); β=-0.0001	-0.04 (-0.17, 0.09); β=-0.002	0.32* (0.04, 0.60); β=0.003	0.0031 (-0.0083, 0.0144); β=0.07	0.01 (-0.03, 0.06); β=0.0008	0.24 (-0.01, 0.49); β=0.002	0.0013 (-0.0091, 0.0118); β=0.0003	0.02 (-0.03, 0.06); β=0.0008
Web browsing	-1.14 (-3.25, 0.96); β=-0.01	-0.0419 (-0.1238, 0.0401); β=-0.001	0.17 (-0.24, 0.57); β=0.009	-0.69 (-1.74, 0.37); β=0.02	0.0010 (-0.0434, 0.0454); β=0.02	-0.05 (-0.24, 0.13); β=0.03	-0.79 (-1.73, 0.15); β=0.02	-0.0072 (-0.0468, 0.0325); β=-0.002	-0.01 (-0.18, 0.15); β=-0.001
Games and comics	-0.17 (-0.35, -0.004); β=-0.002	-0.0057 (-0.0134, 0.0020); β=-0.001	0.01 (-0.03, 0.05); β=0.008	-0.17 (-0.37, 0.04); β=-0.002	-0.0036 (-0.0122, 0.0051); β=-0.08	0.06 (-0.03, 0.16); β=0.0008	-0.18* (-0.32, -0.04); β=-0.002	-0.0054 (-0.0113, 0.0006); β=-0.001	0.01 (-0.01, 0.04); β=0.001
Multimedia	-0.44 (-0.94, 0.06); β=-0.004	-0.0090 (-0.0286, 0.0105); β=-0.002	0.006 (-0.09, 0.10); β=0.0002	0.003 (-0.46, 0.46); β=-0.00002	-0.0007 (-0.0192, 0.0177); β=-0.02	0.01 (-0.06, 0.09); β=-0.0008	-0.15 (-0.49, 0.19); β=-0.001	-0.0048 (-0.0186, 0.0090); β=-0.001	0.02 (-0.04, 0.07); β=0.001
Health	N/A	N/A	N/A	0.38 (-4.38, 5.15); β=0.004	0.0568 (-0.1332, 0.2469); β=1.32	-0.19 (-0.97, 0.59); β=-0.01	0.50 (-4.16, 5.17); β=0.005	0.0611 (-0.1258, 0.2480); β=0.01	-0.20 (-0.98, 0.58); β=-0.01

Camera	3.20 (-4.96, 11.37); β=0.03	-0.0129 (-0.3191, 0.2932); β=-0.003	0.02 (-1.43, 1.48); β=0.001	0.02 (-5.54, 5.58); β=0.0002	0.0568 (-0.1592, 0.2727); β=1.32	-0.22 (-1.10, 0.66); β=-0.01	1.38 (-3.05, 5.80); β=0.01	0.0020 (-0.1695, 0.1736); β=0.0005	0.11 (-0.60, 0.83); β=1.72
Total	-0.12* (-0.23, -0.007); β=-0.001	-0.0029 (-0.0077, 0.0019); β=-0.007	0.01 (-0.02, 0.03); β=0.003	-0.04 (-0.13, 0.04); β=-0.004	-0.0012 (-0.0046, 0.0022); β=-0.03	0.01 (-0.01, 0.02); β=0.0003	-0.07* (-0.14, -0.003); β=-0.007	-0.0024 (-0.0052, 0.0005); β=-0.0006	0.01 (-0.004, 0.02); β=0.0004
Bedtime									
Social network	1.10 (-5.35, 7.55); β=0.01	-0.1152 (-0.3542, 0.1239); β=-0.03	0.45 (-0.73, 1.64); β=0.02	2.38* (0.37, 4.39); β=0.02	-0.0022 (-0.0831, 0.0787); β=-0.05	0.15 (-0.18, 0.48); β=0.008	2.58** (0.60, 4.36); β=0.02	-0.0101 (-0.0861, 0.0659); β=-0.002	0.17 (-0.14, 0.49); β=0.009
Instant messaging	1.77 (-1.38, 4.92); β=0.02	-0.1231 (-0.2512, 0.0050); β=-0.03	0.64* (0.02, 1.25); β=0.03	0.24 (-1.23, 1.70); β=0.002	0.0456 (-0.0122, 0.1033); β=1.06	-0.18 (-0.42, 0.06); β=-0.01	0.59 (-0.73, 1.92); β=-0.006	-0.0049 (-0.0134, 0.0035); β=0.006	-0.06 (-0.28 0.15); β=-0.004
Tools	-4.34 (-10.25, 1.56); β=-0.04	0.1062 (-0.1155, 0.3280); β=0.02	-0.95 (-2.04, 0.14); β=-0.05	-0.86 (-3.25, 1.54); β=-0.008	-0.0460 (-0.1393, 0.0473); β=-1.07	0.13 (-0.25, 0.51); β=0.007	-1.07 (-3.24, 1.11); β=-0.01	-0.0260 (-0.1104, 0.0585); β=-0.006	0.03 (-0.32, 0.38); β=0.002
Web browsing	-3.06 (-9.35, 15.46); β=0.03	0.2611 (-0.1877, 0.7080); β=0.06	-0.94 (-3.18, 1.30); β=-0.05	-1.44 (-6.24, 3.36); β=-0.01	0.1174 (-0.0709, 0.3058); β=2.74	-0.32 (-1.09, 0.45); β=-0.02	-0.73 (-5.12, 3.67); β=-0.007	0.1474 (-0.0246, 0.3195); β=0.03	-0.43 (-1.15, 0.29); β=-0.02
Games and comics	0.42 (-2.17, 3.01); β=0.004	-0.0802 (-0.1835, 0.0232); β=-0.02	0.45 (-0.06, 0.96); β=0.02	1.75 (-0.44, 3.94); β=0.30	0.0128 (-0.0735, 0.0991); β=-0.003	0.09 (-0.27, 0.44); β=0.005	1.40 (-0.31, 3.11); β=0.01	-0.0196 (-0.0879, 0.0486); β=-0.005	0.21 (-0.08, 0.49); β=0.01
Multimedia	-4.00 (-10.78, 2.78); β=-0.04	-0.0100 (-0.2614, 0.2414); β=-0.002	-0.10 (-1.35, 1.16); β=-0.005	0.89 (-1.34, 3.11); β=0.008	-0.0233 (-0.1099, 0.0633); β=-0.54	0.19 (-0.16, 0.54); β=0.01	0.68 (-1.40, 2.77); β=0.006	-0.0200 (-0.1012, 0.0611); β=-0.005	0.16 (-0.18, 0.50); β=0.009
Health	N/A	N/A	N/A	17.22 (-8.78, 43.22); β=0.16	0.5519 (-0.4686, 1.5720); β=12.86	-1.98 (-6.17, 2.21); β=-0.11	17.47 (-8.06, 43.01); β=0.16	0.5678 (-0.4335, 1.5691); β=0.13	-2.03 (-6.22, 2.16); β=-0.11
Camera	-135.36 (-	6.1200 (-	-32.09 (-	-116.63 (-	3.6540 (-	-12.45 (-	-128.41* (-	4.1632 (-	-15.17 (-

	601.04, 330.32); β=-1.27	11.1420, 23.3880); β=1.43	114.94, 50.76); β=-1.73	251.81, 18.54); β=-1.10	1.6020, 8.910); β=-85.20	33.91, 9.01); β=-0.67	255.77, -1.04); β=-1.21	0.8016, 9.1281); β-0.97	35.78, 5.44); β=-0.82
Total	0.59 (-0.96, 2.13); β=0.006	-0.0604 (-0.1219, 0.0010); β=-0.01	0.32* (0.02, 0.62); β=0.02	0.68 (-0.18, 1.54); β=0.006	0.0153 (-0.0188, 0.0494); β=0.36	-0.01 (-0.15, 0.13); β=-0.0004	0.69 (-0.07, 1.45); β=0.006	0.0033 (-0.0271, 0.0337); β=0.0008	0.05 (-0.08, 0.17); β=0.002
During WASO									
Social network	1.82 (-0.91, 4.55); β=0.02	0.0433 (-0.0634, 0.1499); β=0.01	-0.08 (-0.60, 0.45); β=-0.004	-0.02 (-0.63, 0.59); β=-0.0002	-0.0059 (-0.0297, 0.0179); β=-0.14	0.02 (-0.07, 0.12); β=0.001	0.07 (-0.51, 0.65); β=0.0007	-0.0048 (-0.0275, 0.0180); β=-0.001	0.02 (-0.07, 0.12); β=0.001
Instant messaging	0.26 (-0.54, 1.07); β=0.002	0.0119 (-0.0290, 0.0528); β=0.003	-0.06 (-0.24, 0.13); β=-0.003	0.07 (-0.16, 0.29); β=0.0006	-0.0069 (-0.0157, 0.0020); β=-0.16	0.04* (0.001, 0.07); β=0.002	0.06 (-0.16, 0.27); β=0.0006	-0.0049 (-0.0134, 0.0035); β=-0.001	0.03 (-0.01, 0.06); β=0.001
Tools	0.60 (-0.01, 1.22); β=0.006	-0.0018 (-0.0249 0.0213); β=-0.0004	0.06 (-0.05, 0.18); β=0.003	0.04 (-0.30, 0.39); β=0.0004	0.0062 (-0.0074 0.0197); β=0.14	-0.02 (-0.08, 0.03); β=-0.001	0.13 (-0.15, 0.42); β=0.001	0.0060 (-0.0051, 0.0171); β=0.001	-0.02 (-0.06, 0.03); β=-0.001
Web browsing	12.67 (-10.03, 35.37); β=0.12	-0.0062 (-1.2060, 1.1940); β=-0.001	0.53 (-4.47, 5.86); β=0.03	2.13 (-0.19, 4.46); β=0.02	-0.0740 (-0.1655, 0.0175); β=-1.73	0.47* (0.09, 0.84); β=-0.003	2.29* (0.03, 4.55); β=0.02	-0.0725 (-0.1620, 0.0170); β=-0.02	0.46* (0.08, 0.83); β=0.02
Games and comics	0.84 (-0.18, 1.86); β=0.008	0.0095 (-0.0298, 0.0489); β=0.002	0.02 (-0.17, 0.21); β=0.001	0.25 (-0.34, 0.83); β=0.002	-0.0125 (-0.0352, 0.0102); β=-0.29	0.06 (-0.03, 0.16); β=0.003	0.35 (-0.16, 0.86); β=0.003	-0.0086 (-0.0286, 0.0115); β=-0.002	0.05 (-0.03, 0.14); β=0.003
Multimedia	0.13 (-0.89, 1.16); β=0.001	0.0076 (-0.0350, 0.0501); β=0.002	-0.03 (-0.23, 0.17); β=-0.002	1.74 (-0.06, 3.54); β=0.02	-0.0291 (-0.0992, 0.0409); β=-0.68	0.28 (-0.01, 0.57); β=0.02	-0.13 (-0.81, 0.54); β=-0.001	0.0027 (-0.0247, 0.0302); β=0.0006	-0.01 (-0.12, 0.11); β=-0.004
Health	N/A	N/A	N/A	6.39 (-20.66, 33.45); β=0.06	0.9240 (-0.1309, 1.9740); β=21.52	-3.64 (-7.95, 0.68); β=-0.20	6.65 (-19.94, 33.24); β=0.06	0.9387 (-0.0969, 1.9743); β=0.22	-3.68 (-8.00, 0.65); β=-0.20
Camera	286.27 (-136.42,	-13.5600 (-29.1660,	97.43* (23.21,	157.39* (37.41,	-3.4020 (-8.1900,	25.79* (6.22,	171.80** (58.75,	-4.2466 (-8.7582,	31.94** (13.21,

	708.96); β=2.69	2.0460); β=-3.16	171.65); β=5.25	277.37); β=1.48	1.3920); β=-79.27	45.36); β=1.39	284.85); β=1.61	0.2651); β=-0.99	50.66); β=0.006
Total	0.11 (-0.16, 0.37); β=0.001	0.0130* (0.0028, 0.0232); β=0.003	-0.05* (-0.10, -0.005); β=-0.003	0.02 (-0.13, 0.18); β=0.0002	-0.0038 (-0.0098, 0.0023); β=-0.08	0.02 (-0.01, 0.04); β=0.001	0.04 (-0.09, 0.18); β=0.004	-0.0006 (-0.0059, 0.0047); β=-0.0001	0.005 (-0.02, 0.03); β=0.0002

* / ** / *** significant at 5% / 1% / 0.1% level

WASO: wake after sleep onset; β: standardized coefficient

Table 4. Multilevel regression results (reported as coefficient (95% confidence interval)) of smartphone usage (min) on physical activity level (number of participants=187, number of days=1,106)

	Secondary school students (number of participants=32, number of days=176)		University students (number of participants=155, number of days=930)		Overall (number of participants=187, number of days=1,106)	
	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)
Daytime						
Social network	10.49 (-11.04, 32.02); β=0.002	0.12 (-0.27, 0.51); β=0.001	13.52* (0.94, 26.11); β=0.003	0.27* (0.06, 0.48); β=0.003	10.70* (0.30, 21.10); β=0.002	0.21* (0.03, 0.39); β=0.002
Instant messaging	25.89* (5.96, 45.82); β=0.005	0.37* (0.01, 0.72); β=0.004	6.46* (1.03, 11.90); β=0.001	0.09 (-0.01, 0.18); β=0.0002	8.53** (3.13, 13.92); β=0.002	0.11* (0.02, 0.20); β=0.001
Tools	32.50 (-4.02, 69.01); β=0.007	0.72* (0.08, 1.36); β=-0.008	1.27 (-6.94, 14.16); β=0.0003	-0.02 (-0.21, 0.16); β=-0.0003	4.13 (-6.44, 14.70); β=0.001	0.03 (-0.15, 0.21); β=0.0003
Web browsing	77.94 (-32.26, 188.13); β=0.02	0.94 (-0.98, 2.88); β=0.01	22.77 (-19.82, 65.37); β=0.005	0.29 (-0.46, 1.03); β=0.003	32.85 (-8.17, 73.87); β=0.007	0.31 (-0.39, 1.03); β=0.004
Games and comics	5.35 (-4.76, 15.45); β=0.001	-0.001 (-0.18, 0.18); β=-0.000001	0.77 (-7.55, 9.08); β=0.0002	0.02 (-0.12, 0.16); β=0.002	3.25 (-2.82, 9.32); β=0.001	0.01 (-0.09, 0.12); β=0.0002
Multimedia	25.69* (0.11, 51.26); β=0.005	0.50* (0.05, 0.94); β=0.006	7.27 (-10.87, 25.41); β=0.001	0.14 (-0.16, 0.43); β=0.002	14.41* (0.14, 28.68); β=0.003	0.32** (0.08, 0.55); β=0.004
Health	N/A	N/A	-9.45 (-198.77, 179.87); β=-0.002	-0.04 (-3.15, 3.06); β=-0.001	-2.01 (-199.72, 195.41); β=-0.0004	-0.07 (-3.35, 3.20); β=-0.001
Camera	-100.56 (-500.55, 299.42); β=-0.02	-1.96 (-8.93, 5.01); β=-0.02	17.52 (-200.06, 235.10); β=0.004	0.17 (-3.34, 3.68); β=0.002	-43.90 (-224.51, 136.71); β=-0.009	-31.40 (-116.22, 53.41); β=-0.26
Total	7.15* (1.02, 13.28); β=0.001	0.09 (-0.02, 0.20); β=0.001	3.52* (0.37, 6.66); β=0.001	0.05 (-0.001, 0.11); β=0.001	4.55* (1.77, 7.34); β=0.001	0.06* (0.01, 0.11); β=0.001
Bedtime						
Social network	-88.62 (-400.75, 223.50); β=-0.02	-1.28 (-6.74, 4.17); β=-0.01	-52.87 (-130.75, 25.01); β=-0.01	-0.48 (-1.75, 0.80); β=-0.005	-51.75 (-127.92, 24.43); β=-0.01	-0.46 (-1.72, 0.80); β=-0.005
Instant messaging	-66.99 (-233.06, 99.08); β=-0.01	-1.24 (-4.17, 1.68); β=-0.01	-25.11 (-82.23, 32.01); β=-0.005	0.34 (-0.59, 1.27); β=0.004	-23.17 (-77.54, 31.21); β=-0.005	0.29 (-0.61, 1.19); β=0.003
Tools	190.96 (-108.27, 490.19); β=0.04	4.12 (-1.06, 9.31); β=0.05	-57.54 (-152.49, 37.40); β=-0.01	-0.93 (-2.46, 0.60); β=-0.001	-34.38 (-124.87, 56.10); β=-0.007	-0.72 (-2.20, 0.76); β=-0.01

Web browsing	148.88 (-469.21, 766.97); β=0.03	4.40 (-6.36, 15.15); β=0.05	-29.05 (-217.86, 159.76); β=-0.006	0.07 (-3.01, 3.15); β=0.001	-3.64 (-184.89, 177.61); β=-0.0007	0.94 (-2.05, 3.93); β=0.01
Games and comics	-58.44 (-193.35, 76.46); β=-0.01	-0.26 (-2.60, 2.15); β=-0.003	-48.06 (-134.14, 38.01); β=-0.01	-1.11 (-2.52, 0.31); β=-0.01	-48.90 (-119.89, 22.10); β=-0.01	-0.66 (-1.85, 0.52); β=-0.007
Multimedia	-3.92 (-336.54, 328.71); β=-0.001	2.03 (-3.74, 7.81); β=0.02	10.16 (-76.11, 96.43); β=0.002	0.17 (-1.22, 1.56); β=0.002	5.39 (-78.81, 89.59); β=0.001	0.22 (-1.17, 1.60); β=0.002
Health	N/A	N/A	-665.89 (-1683.57, 351.78); β=-0.13	-11.01 (-27.43, 5.40); β=-0.12	-694.69 (-1749.65, 360.26); β=-0.14	-11.68 (-28.98, 5.62); β=-0.13
Camera	5238.15 (-19576.76, 30053.05); β=1.04	65.51 (-368.41, 499.43); β=0.73	-3562.48 (-8812.56, 1687.60); β=-0.71	-44.60 (-129.43, 40.23); β=-0.50	-2553.19 (-7715.52, 2609.14); β=-0.51	-31.40 (-116.22, 53.41); β=-0.35
Total	-13.78 (-94.63, 67.07); β=-0.003	0.10 (-1.32, 1.52); β=0.001	-26.24 (-59.56, 7.08); β=-0.005	-0.13 (-0.68, 0.41); β=-0.002	-24.52 (-55.58, 6.54); β=-0.005	-0.09 (-0.61, 0.42); β=-0.001
During WASO						
Social network	39.49 (-111.49, 190.47); β=0.008	-0.01 (-2.66, 2.65); β=-0.0001	2.97 (-20.79, 26.72); β=0.001	0.01 (-0.38, 0.39); β=0.0001	4.85 (-18.89, 28.60); β=0.001	0.02 (-0.37, 0.41); β=0.0003
Instant messaging	29.84 (-12.52, 72.21); β=0.006	0.65 (-0.10, 1.40); β=0.007	6.27 (-2.45, 14.99); β=0.001	0.02 (-0.13, 0.16); β=0.001	6.97 (-1.70, 15.65); β=0.001	0.04 (-0.10, 0.19); β=0.001
Tools	-20.04 (-50.82, 10.75); β=-0.004	-0.38 (-0.92, 0.15); β=-0.004	7.16 (-6.54, 20.86); β=0.001	0.06 (-0.16, 0.28); β=0.001	3.24 (-.67, 15.15); β=0.001	0.05 (-0.14, 0.25); β=0.001
Web browsing	1153.07* (57.92, 2248.22); β=0.23	1.04 (-1.94, 4.03); β=0.25	-82.60 (-173.48, 8.29); β=-0.02	-1.24 (-2.72, 0.24); β=-0.01	-71.19 (-164.38, 21.99); β=0.01	-1.02 (-2.56, 0.53); β=-0.01
Games and comics	31.90 (-19.90, 83.70); β=0.006	0.65 (-0.25, 1.55); β=0.007	-12.29 (-35.11, 10.53); β=-0.002	-0.15 (-0.51, 0.22); β=-0.002	-4.96 (-25.88, 15.97); β=-0.001	0.04 (-0.30, 0.38); β=-0.001
Multimedia	21.64 (-28.92, 72.20); β=0.004	-0.12 (-1.00, 0.76); β=-0.001	-41.90 (-112.46, 28.67); β=-0.008	-0.64 (-1.78, 0.50); β=-0.007	14.84 (-11.85, 41.53); β=0.003	0.06 (-0.38, 0.50); β=0.001
Health	N/A	N/A	9.40 (-1048.04, 1066.83); β=0.002	-1.95 (-19.01, 15.12); β=-0.02	37.94 (-1050.20, 1126.09); β=0.008	-1.73 (-19.58, 16.12); β=-0.02
Camera	-3407.19 (-23839.59, 17025.20); β=-0.68	-83.94 (-439.96, 272.08); β=-0.94	-1432.84 (-6071.19, 3205.02); β=-0.29	-18.54 (-94.34, 57.27); β=-0.21	-43.90 (-224.51, 136.71); β=-0.27	-0.72 (-3.68, 2.24); β=-0.26
Total	6.87 (-6.90,	0.09 (-0.15,	3.42 (-2.58,	-0.003 (-0.10,	4.07 (-1.42,	0.02 (-0.07,

	20.63); β=0.0014	0.33); β=0.001	9.42); β=0.001	0.09); β=-0.00003	9.56); β=0.001	0.11); β=0.0003

* / ** / *** significant at 5% / 1% / 0.1% level

WASO: wake after sleep onset; *β*: standardized coefficient

Table 5. Multilevel regression results (reported as coefficient (95% confidence interval)) of sleep quality on physical activity level (number of participants=352, number of days=1,517)

	Secondary school students (number of participants=123, number of days=459)		University students (number of participants=229, number of days=1,058)		Overall (number of participants=352, number of days=1,517)	
	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)
Total sleeping time (hr)	-706.06*** (-932.24, -479.89); β=-0.14	-10.83*** (-15.12, -6.54); β=-0.12	-569.76*** (-700.71, -438.80); β=-0.11	-7.95*** (-10.16, -5.74); β=-0.09	-615.80*** (-730.82, -500.79); β=-0.12	-8.56*** (-10.58, -6.54); β=-0.10
Sleep efficiency (%)	-112.44* (12.55, 212.33); β=0.02	2.29* (0.34, 4.25); β=0.03	-1.82 (-62.24, 58.61); β=-0.0004	-0.40 (-1.41, 0.61); β=-0.005	-30.33 (-21.93, 82.59); β=0.006	0.33 (-0.60, 1.26); β=0.004
Wake after sleep onset (min)	-42.74*** (-65.12, -20.37); β=-0.01	-0.76* (-1.19, -0.33); β=-0.01	-15.28* (-29.15, -1.42); β=-0.003	-0.13 (-0.36, 0.10); β=-0.002	-22.96*** (-34.86, -11.07); β=-0.005	-0.29** (-0.51, -0.08); β=-0.003

* / ** / *** significant at 5% / 1% / 0.1% level

β: standardized coefficient

Table 6. Multilevel regression results (reported as coefficient (95% confidence interval)) of sleep quality on daytime smartphone usage (number of participants=187, number of days=689)

Secondary school students (number of participants =32, number of days=92)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	1.57 (-2.28, 5.41); β=0.001	0.74 (-5.66, 7.13); β=0.0002	-0.74 (-3.90, 2.43); β=-0.0004	0.95 (-0.17, 2.07); β=0.002	0.80 (-11.62, 13.22); β=0.0002	0.43 (-3.29, 4.16); β=0.0004	N/A	0.14 (-0.21, 0.50); β=0.002	0.80 (-18.35, 19.96); β=0.0001
Sleep efficiency (%)	-57.28, (-163.00, 48.45); β=-3.20	-54.80 (-219.55, 109.95); β=-1.64	22.13 (-51.77, 96.02); β=1.33	15.51 (-11.40, 42.42); β=2.97	-119.35 (-450.26, 211.56); β=-3.68	27.79 (-61.91, 117.48); β=2.45	N/A	-0.88 (-9.15, 7.39); β=-0.98	-228.25 (-720.28, 263.79); β=-3.47
Wake after sleep onset (min)	9.92 (-11.63, 31.47); β=0.006	15.41 (-18.73, 49.54); β=0.004	-5.46 (-21.46, 10.53); β=-0.003	-0.70 (-6.53, 5.13); β=-0.001	38.90 (-28.42, 106.22); β=0.01	-0.75 (-20.04, 18.53); β=-0.001	N/A	0.41 (-1.38, 2.19); β=0.005	62.58 (-39.75, 164.91); β=0.01
University students (number of participants =155, number of days=598)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.15 (-0.84, 1.14); β=0.0001	-1.02 (-3.51, 1.47); β=-0.0003	-1.00 (-2.28, 0.27); β=-0.001	-0.26 (-0.57, 0.05); β=-0.0005	1.39 (-0.14, 2.91); β=0.0004	0.49 (-0.31, 1.29); β=0.0004	0.03 (-0.05, 0.10); β=0.0003	0.003 (-0.07, 0.07); β=0.00004	-0.78 (-4.90, 3.35); β=-0.0001
Sleep efficiency (%)	4.69, (-21.19, 30.58); β=0.26	-6.82 (-70.00, 56.36); β=-0.20	-1.39 (-34.45, 31.66); β=-0.08	-9.42* (-17.50, -1.33); β=-1.80	22.30 (-17.14, 61.74); β=0.69	3.73 (-16.74, 24.40); β=0.33	-0.07 (-1.99, 1.85); β=-0.08	0.89 (-0.82, 2.61); β=0.99	-2.80 (-103.16, 108.77); β=0.04

Wake after sleep onset (min)	-0.29 (-6.58, 6.01); β=-0.0002	-0.68 (-16.12, 14.76); β=-0.0002	-0.24 (-8.29, 7.81); β=-0.0001	1.10 (-0.87, 3.07); β=0.002	-4.34 (-13.96, 5.28); β=-0.001	1.17 (-3.87, 6.21); β=0.001	0.13 (-0.34, 0.59); β=0.001	-0.24 (-0.66, 0.17); β=-0.003	-1.57 (-27.41, 24.27); β=-0.0002
Overall (number of participants =187, number of days=689)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.23 (-0.80, 1.26); β=0.0001	-0.82 (-3.14, 1.49); β=-0.002	-1.05 (-2.24, 0.14); β=-0.001	-0.10 (-0.41, 0.21); β=-0.0002	1.05 (-0.97, 3.08); β=0.0003	0.47 (-0.40, 1.34); β=0.0004	0.03 (-0.04, 0.09); β=0.0003	0.02 (-0.06, 0.09); β=0.0002	-0.63 (-4.91, 3.65); β=-0.0001
Sleep efficiency (%)	-2.72, (-29.61, 24.16); β=-0.15	-11.92 (-70.63, 46.78); β=-0.36	-0.27 (-30.99, 30.44); β=-0.02	-6.74 (-14.80, 1.31); β=-1.29	13.16 (-39.57, 65.89); β=0.41	6.23 (-15.90, 28.36); β=0.55	-0.06 (-1.74, 1.61); β=-0.08	0.61 (-1.21, 2.43); β=0.68	-20.29 (-130.30, 89.71); β=-0.31
Wake after sleep onset (min)	0.90 (-5.50, 7.29); β=0.001	1.48 (-12.59, 15.16); β=0.0004	-0.74 (-8.07, 6.59); β=-0.0004	0.93 (-0.99, 2.85); β=0.002	0.42 (-12.14, 12.99); β=0.0001	0.81 (-4.49, 6.12); β=0.001	0.10 (-0.30, 0.51); β=0.001	-0.13 (-0.56, 0.31); β=-0.001	7.34 (-18.94, 33.63); β=0.001

* / ** / *** significant at 5% / 1% / 0.1% level

β: standardized coefficient

Figure S1. Histogram of the regression residuals of smartphone usage on total sleeping time, secondary school students

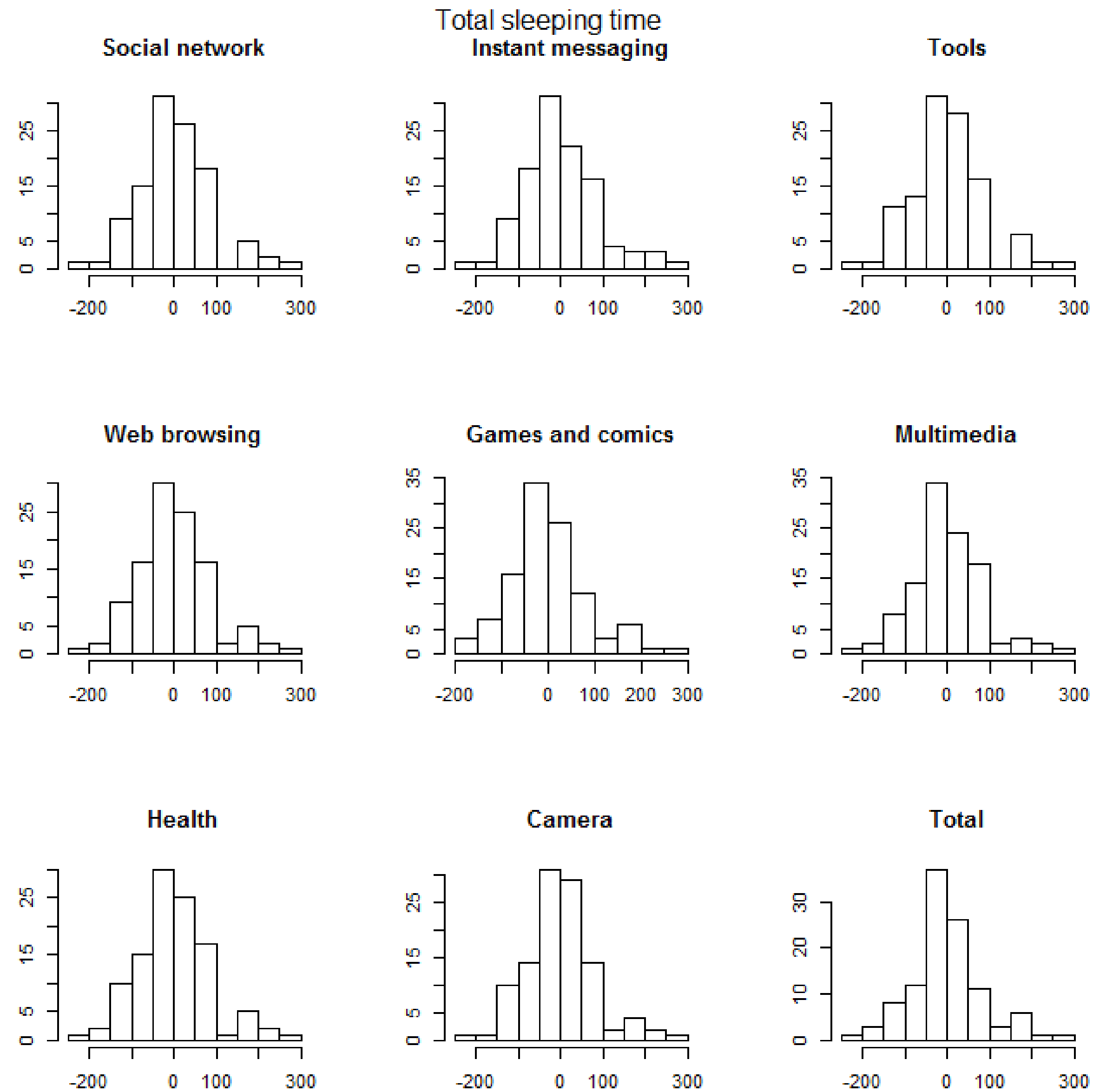

Figure S2. Histogram of the regression residuals of smartphone usage on sleep efficiency, secondary school students

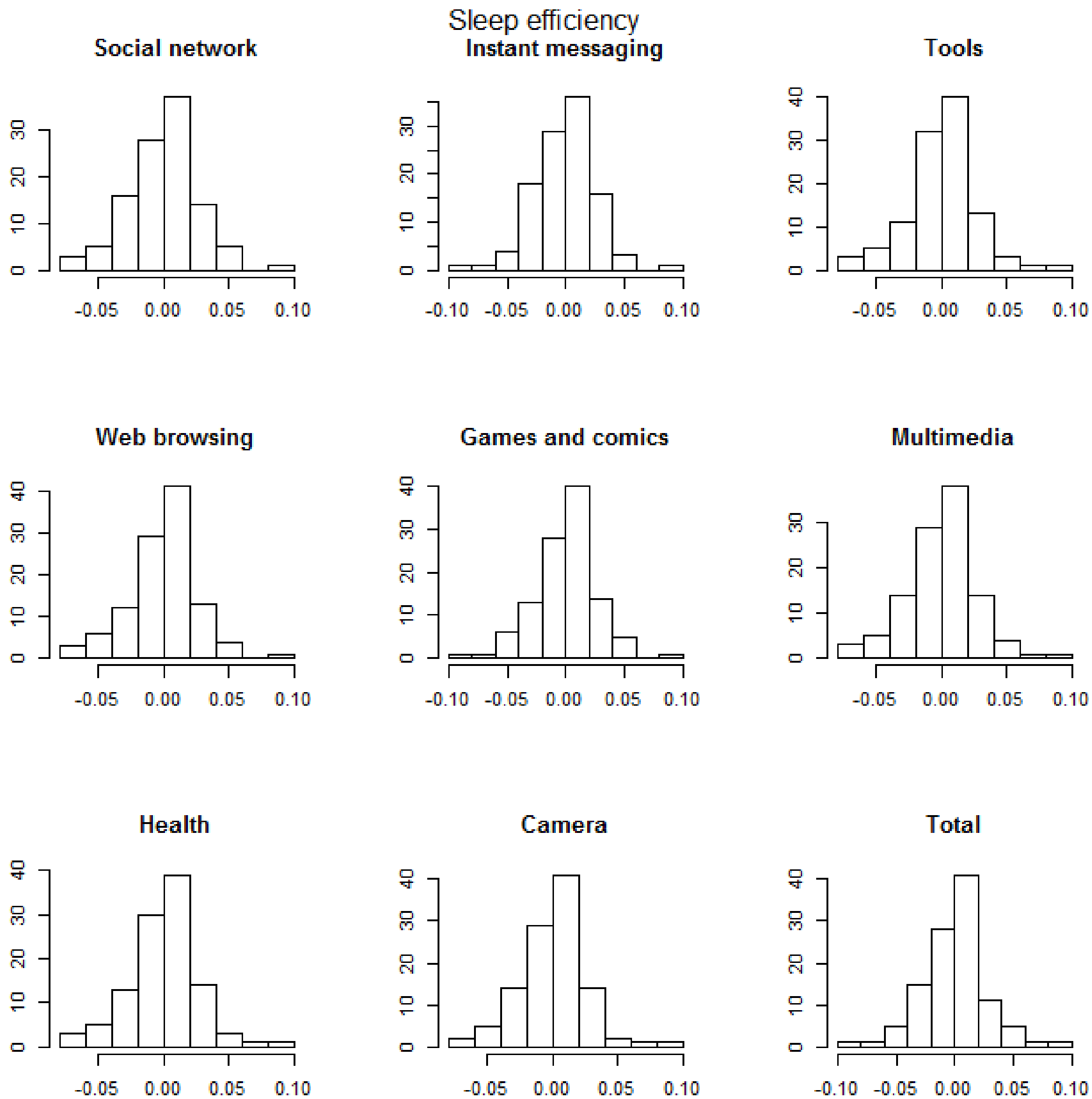

Figure S3. Histogram of the regression residuals of smartphone usage on wake after sleep onset, secondary school students

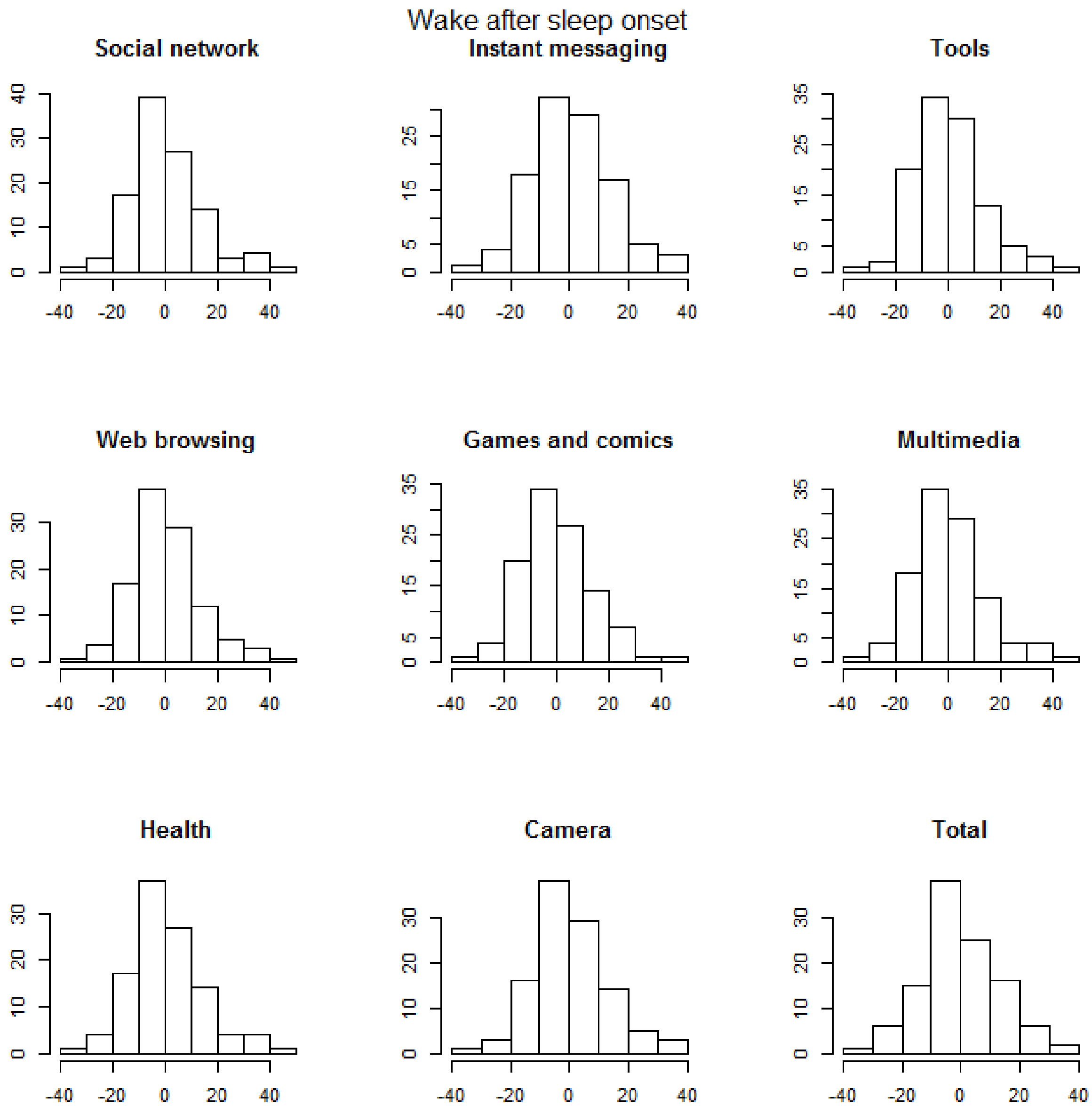

Figure S4. Histogram of the regression residuals of smartphone usage on number of steps, secondary school students

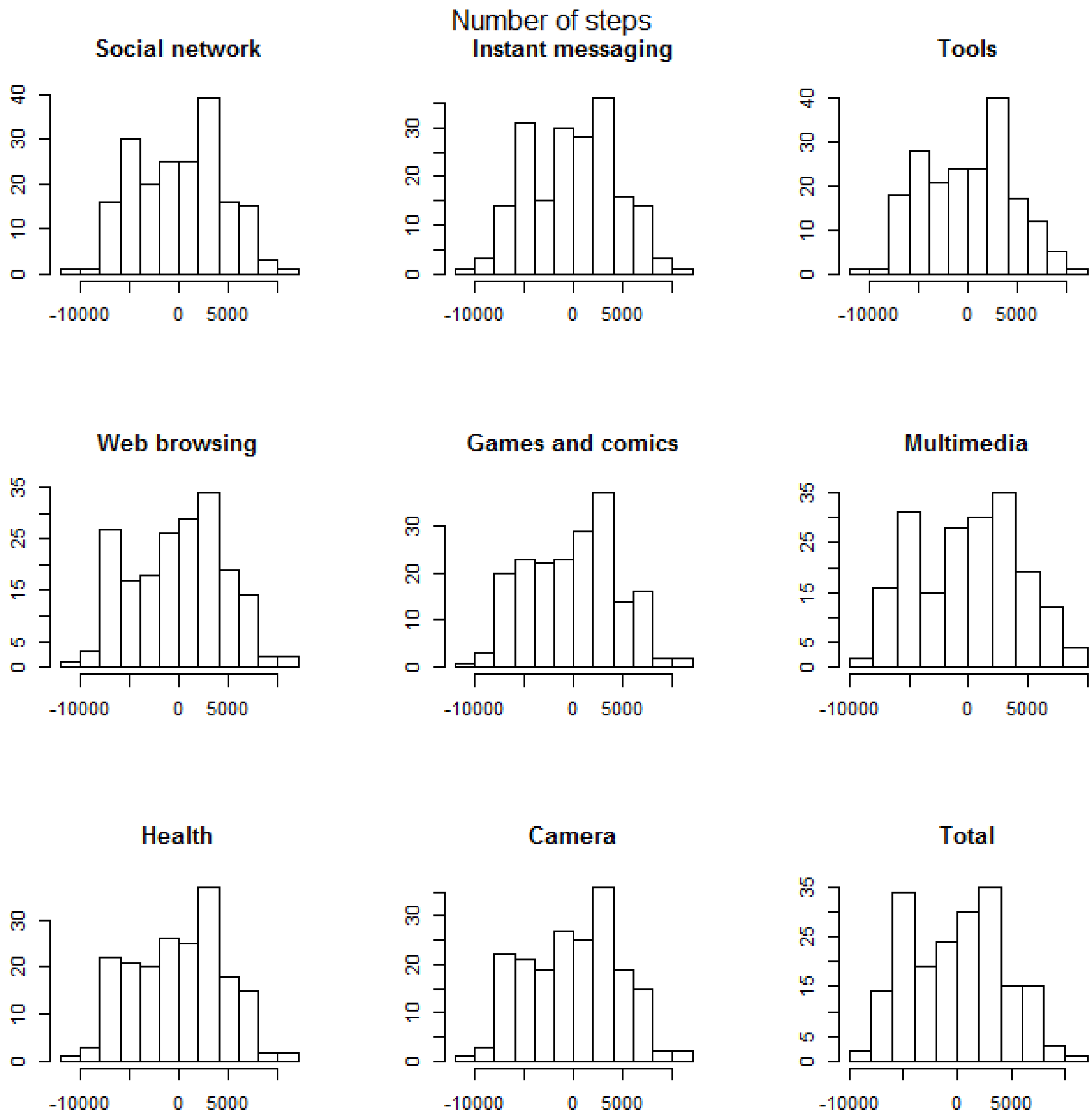

Figure S5. Histogram of the regression residuals of smartphone usage on moderate-to-vigorous physical activity, secondary school students

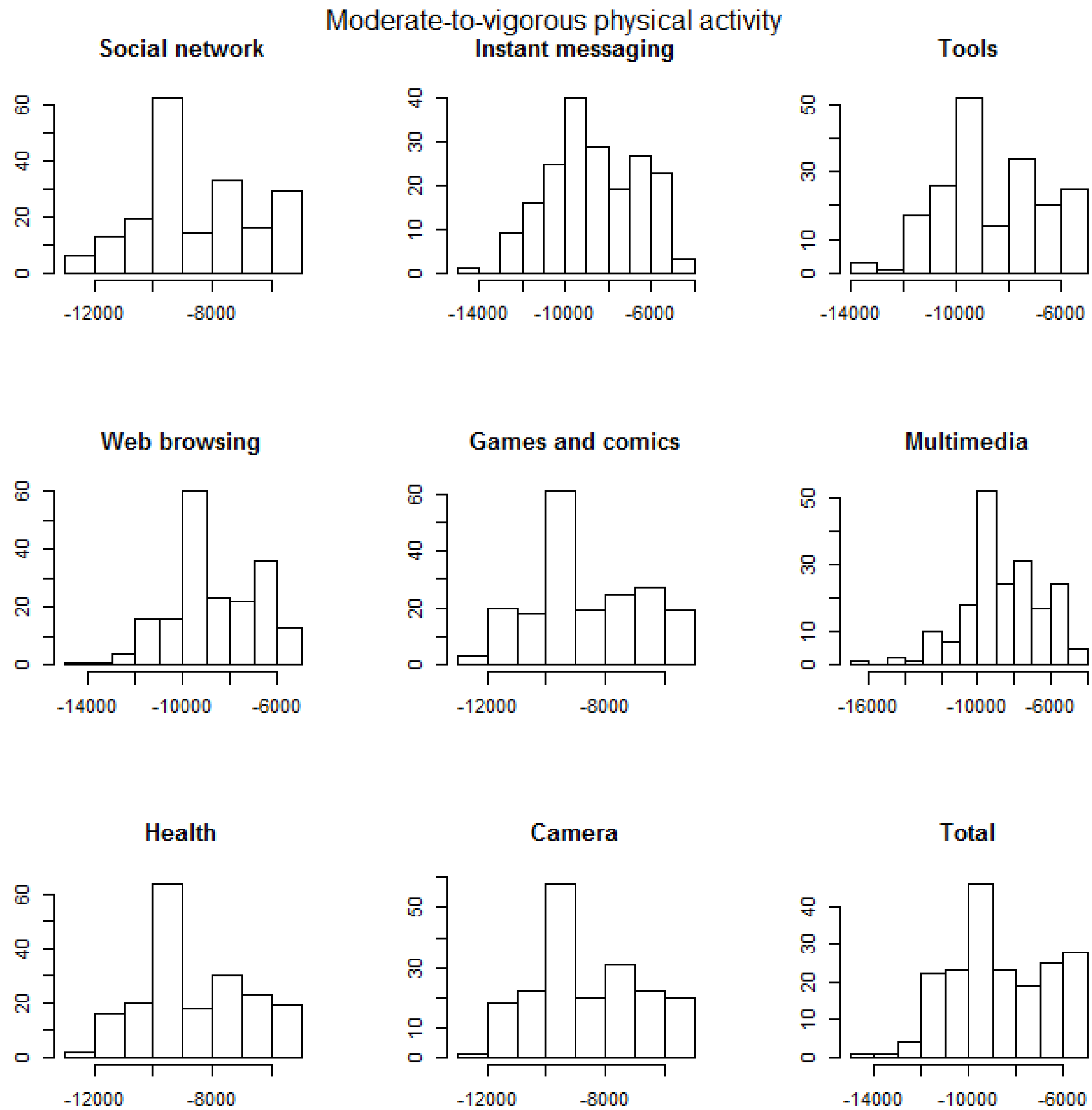

Figure S6. Histogram of the regression residuals of sleep quality on number of steps, secondary school students

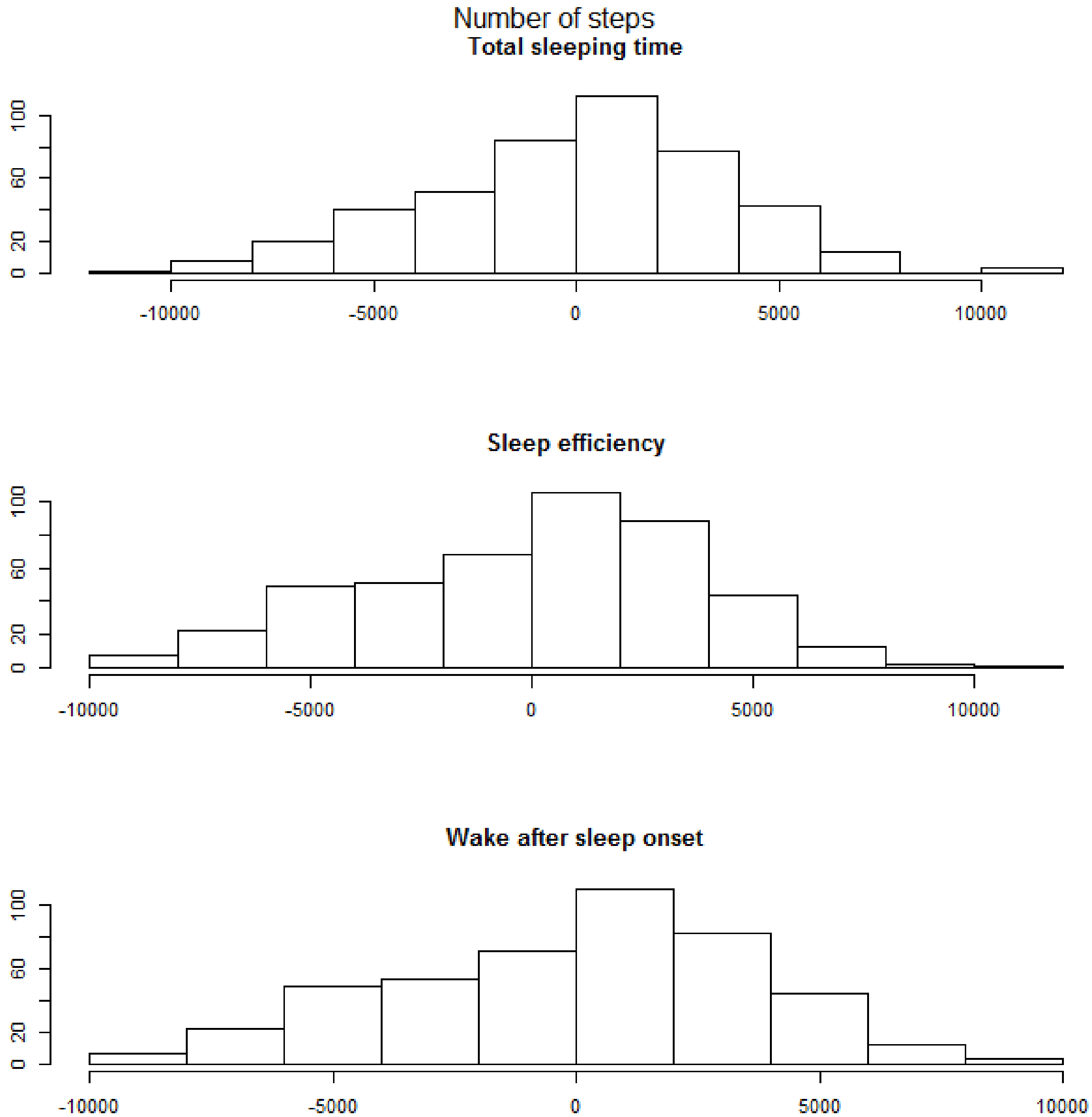

Figure S7. Histogram of the regression residuals of sleep quality on moderate-to-vigorous physical activity, secondary school students

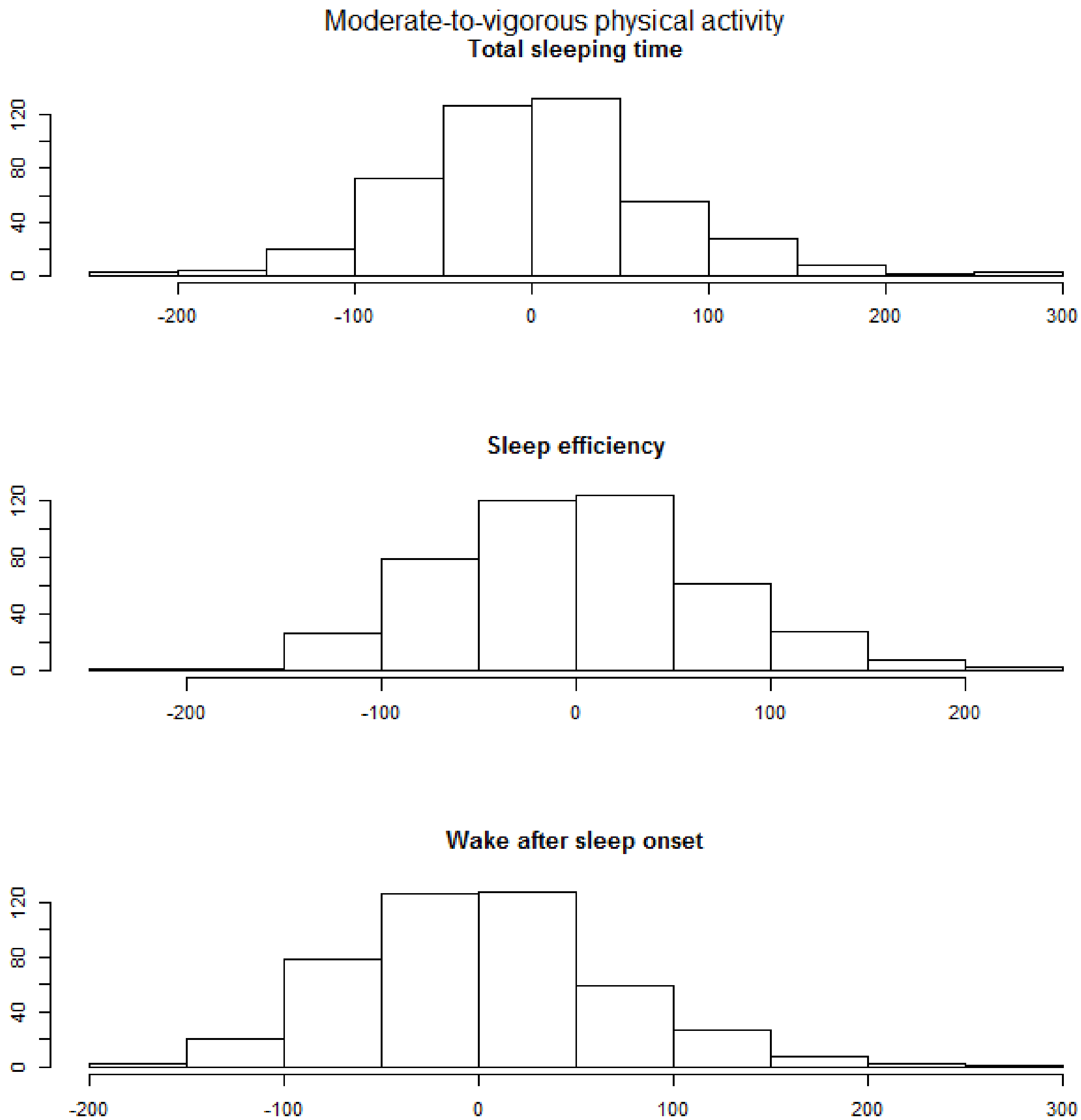

Figure S8. Residual plot of daytime smartphone use on total sleeping time, secondary school students

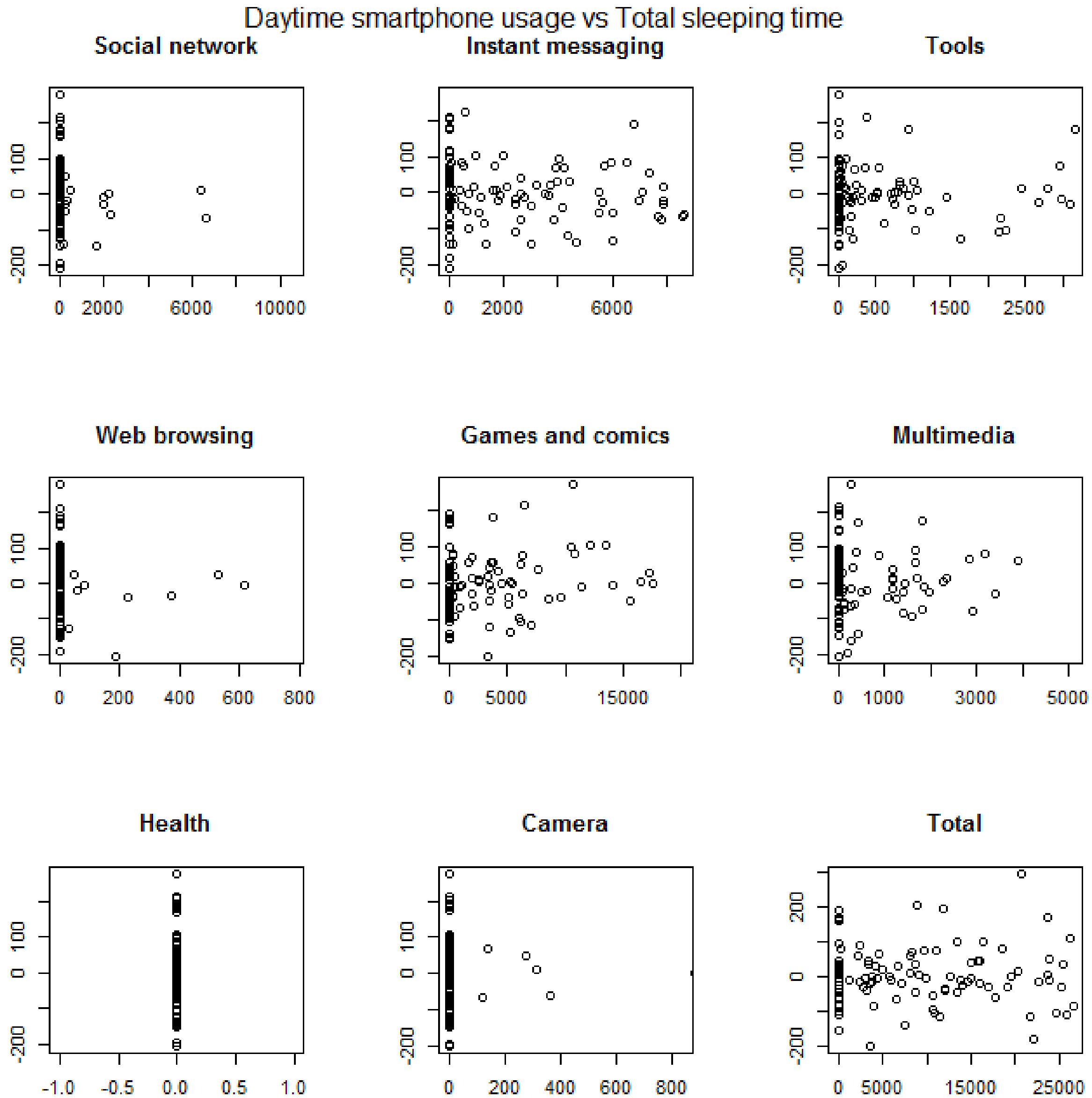

Figure S9. Residual plot of bedtime smartphone use on total sleeping time, secondary school students

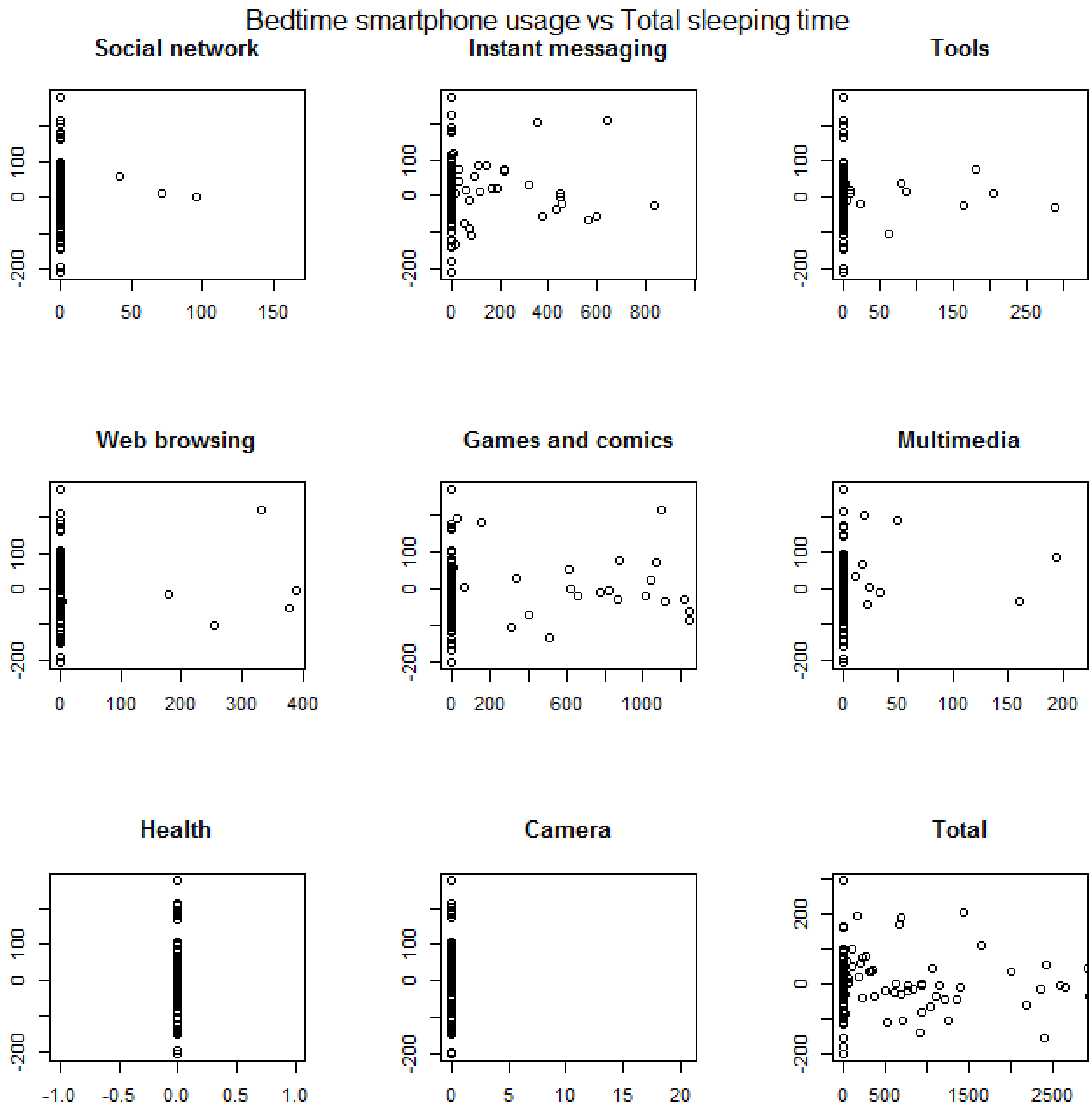

Figure S10. Residual plot of smartphone use during sleep on total sleeping time, secondary school students

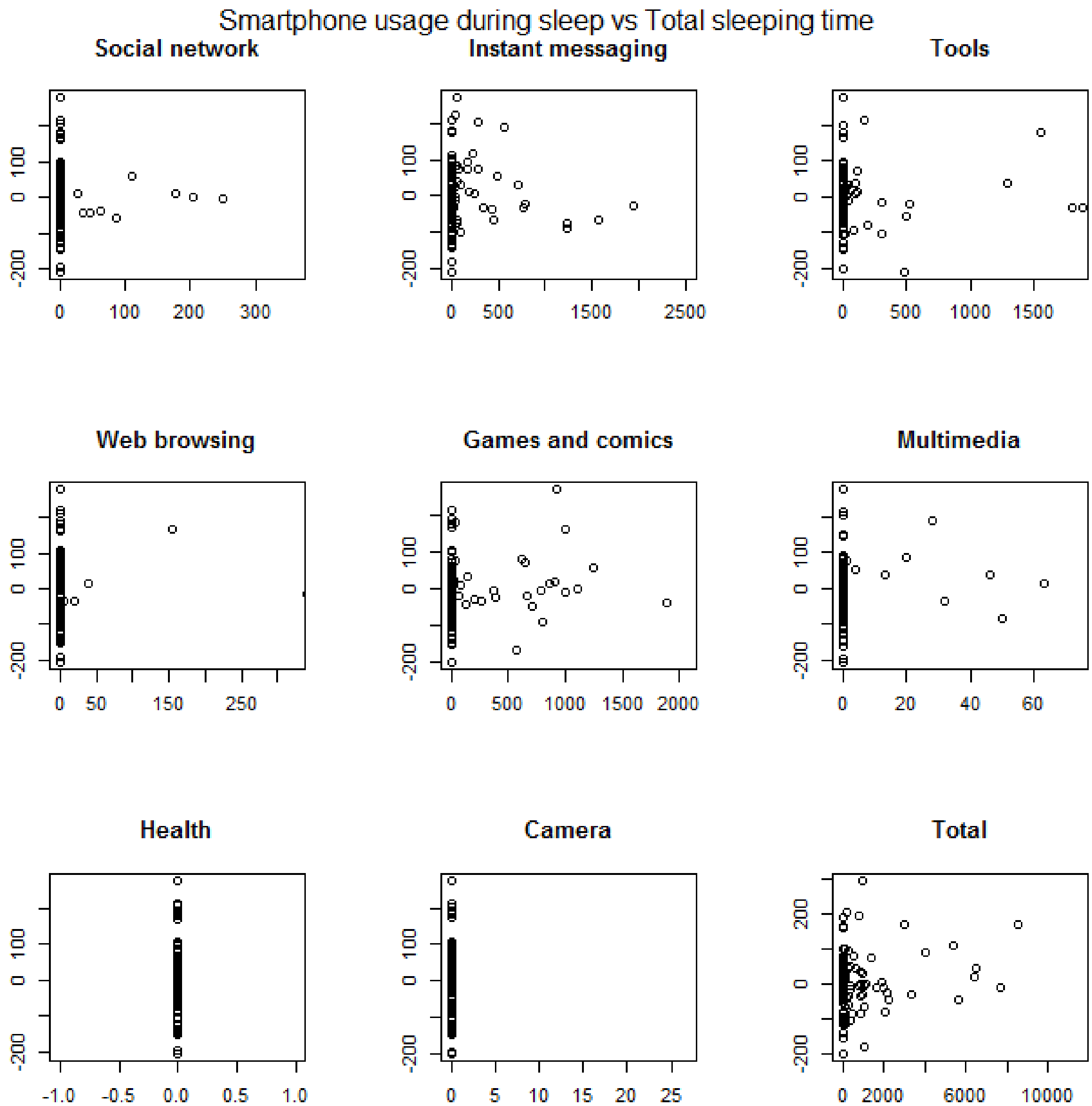

Figure S11. Residual plot of daytime smartphone use on sleep efficiency, secondary school students

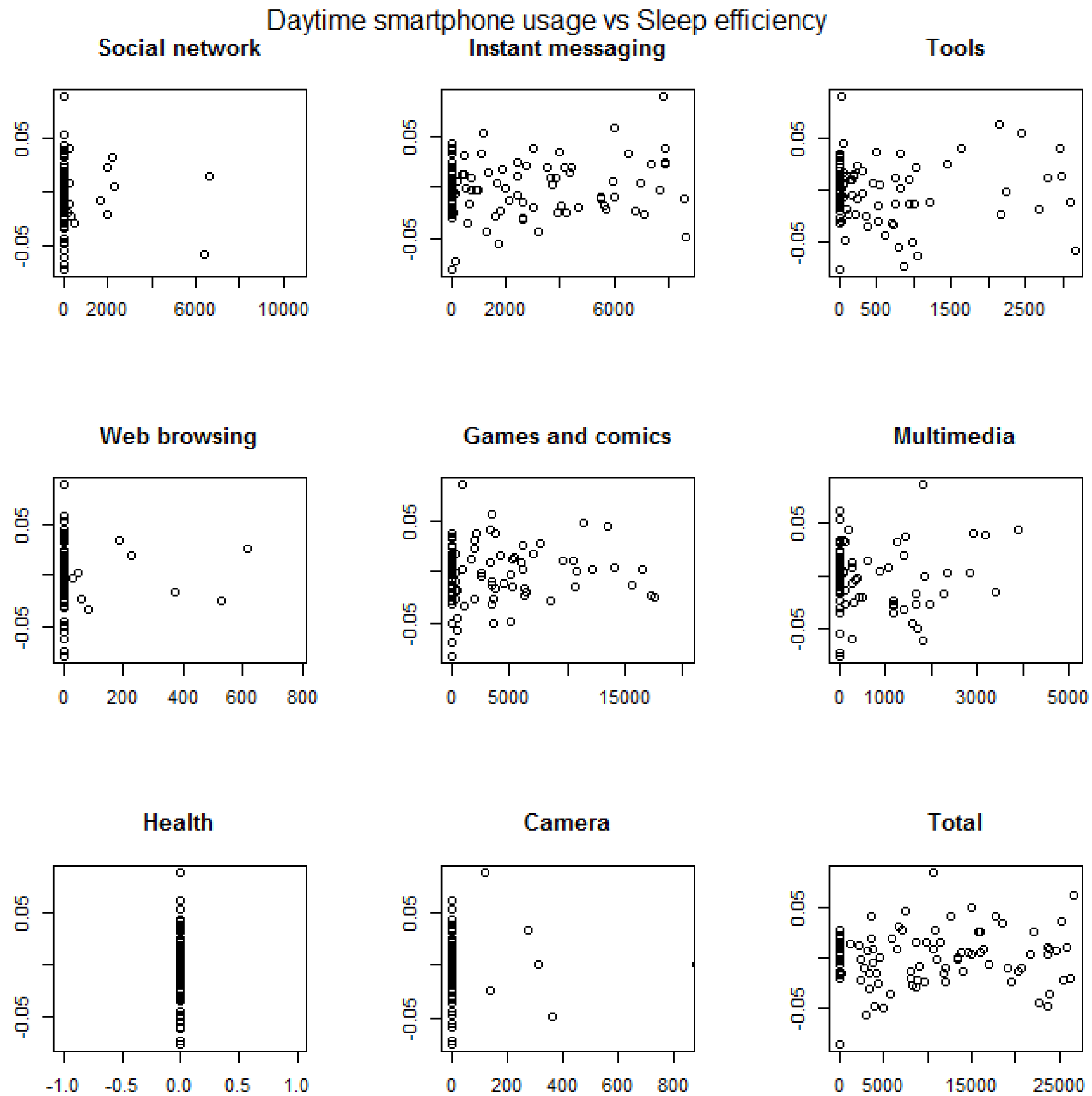

Figure S12. Residual plot of bedtime smartphone use on sleep efficiency, secondary school students

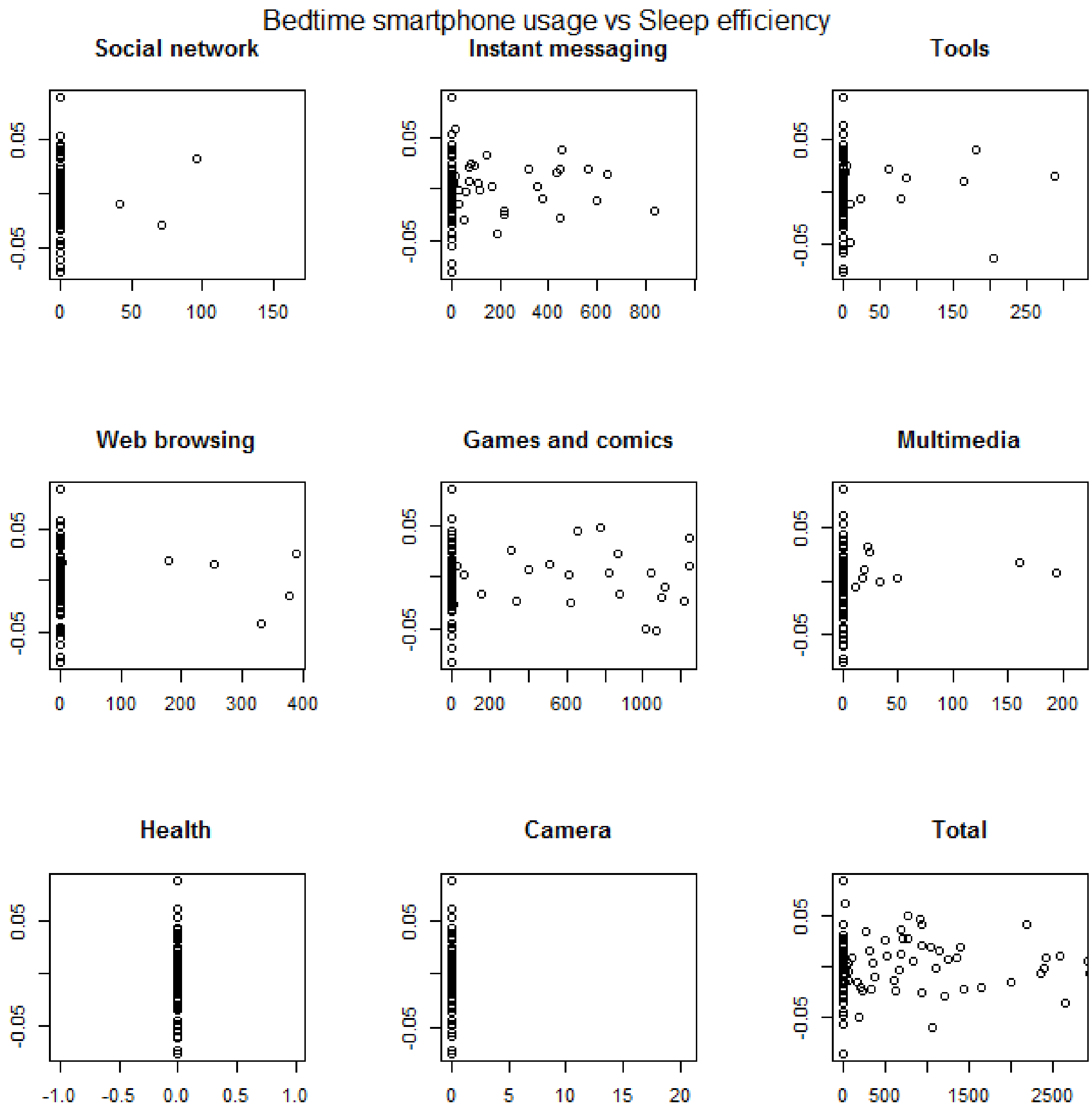

Figure S13. Residual plot of smartphone use during sleep on sleep efficiency, secondary school students

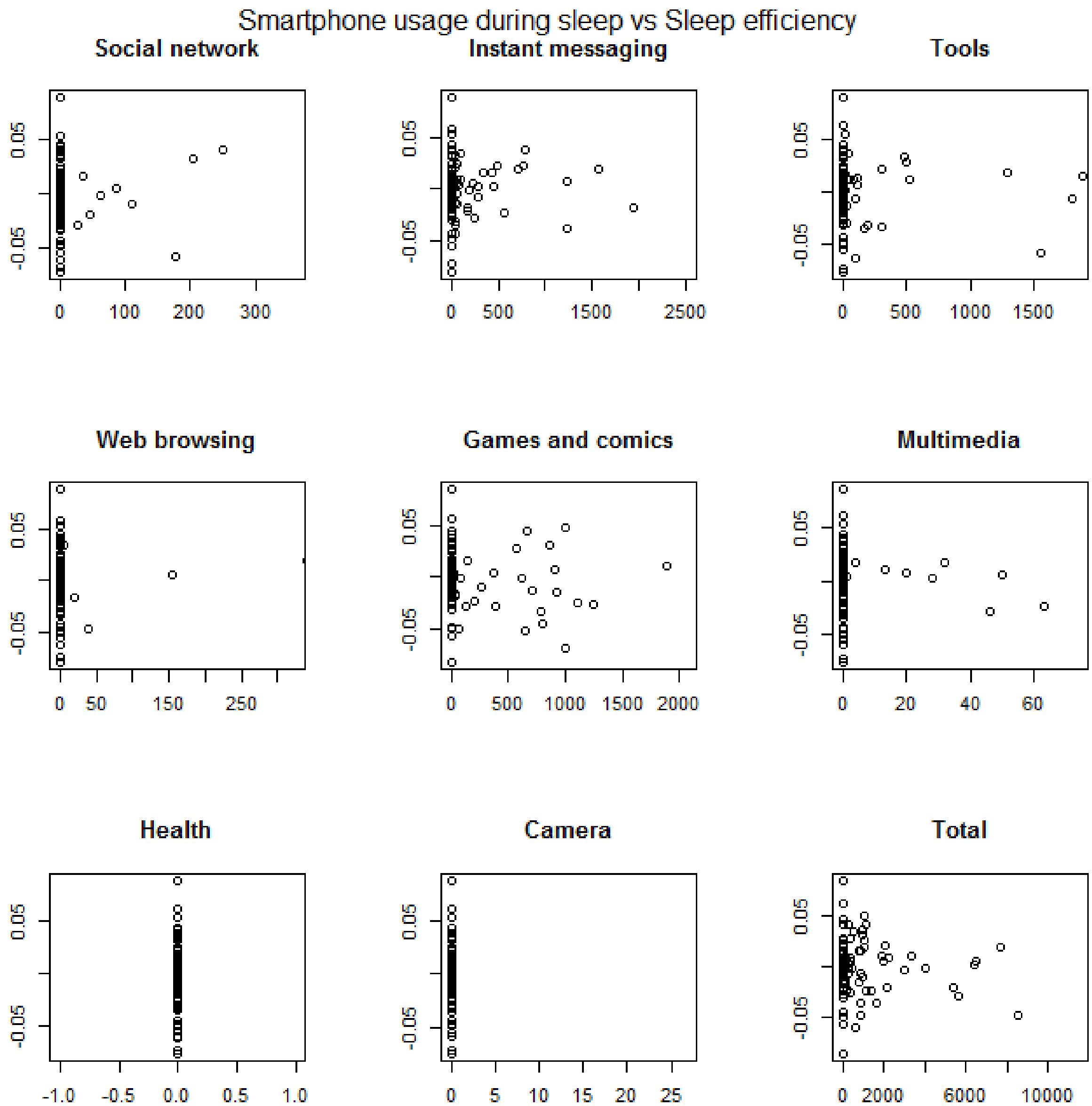

Figure S14. Residual plot of daytime smartphone use on wake after sleep onset, secondary school students

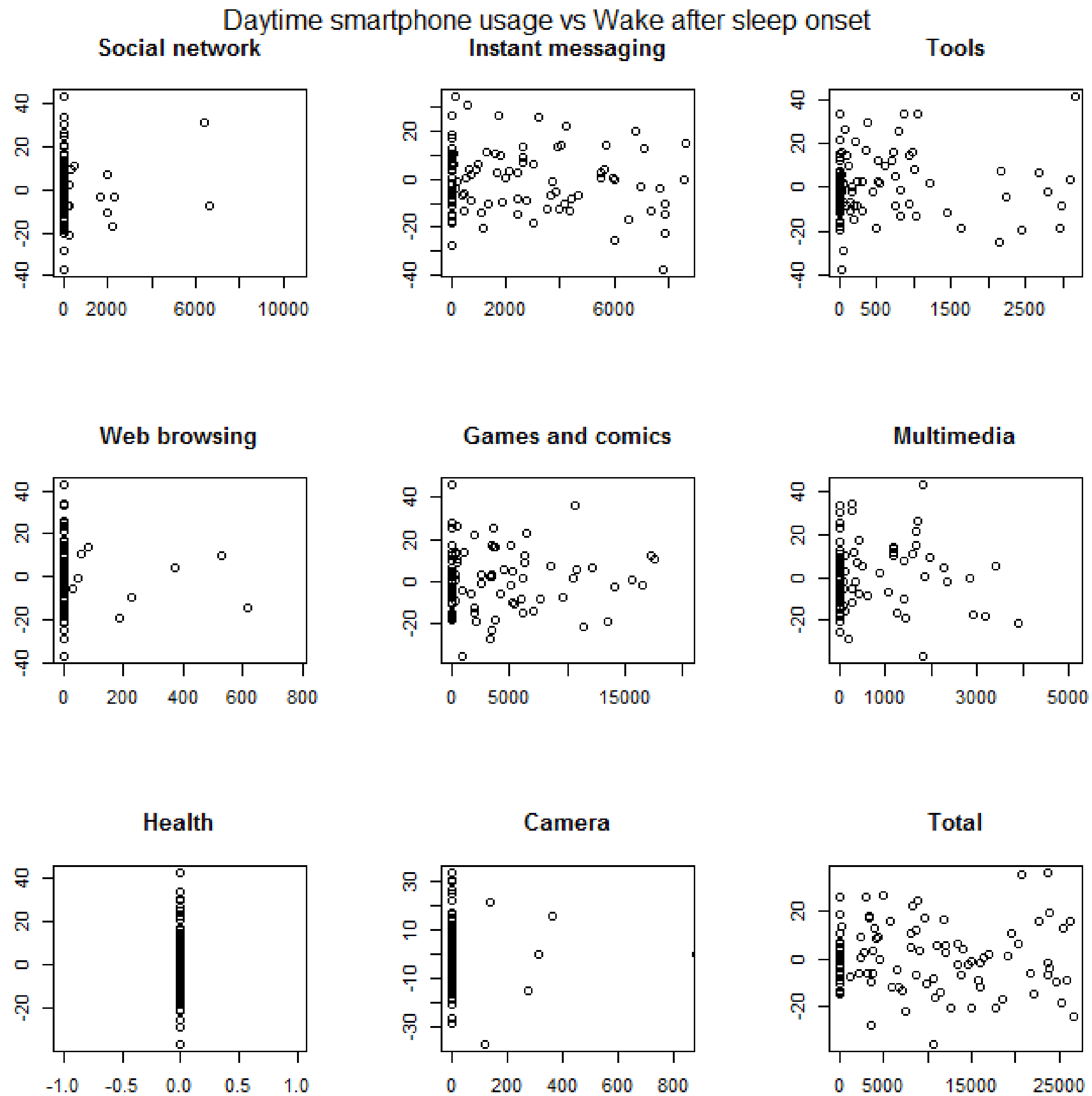

Figure S15. Residual plot of bedtime smartphone use on wake after sleep onset, secondary school students

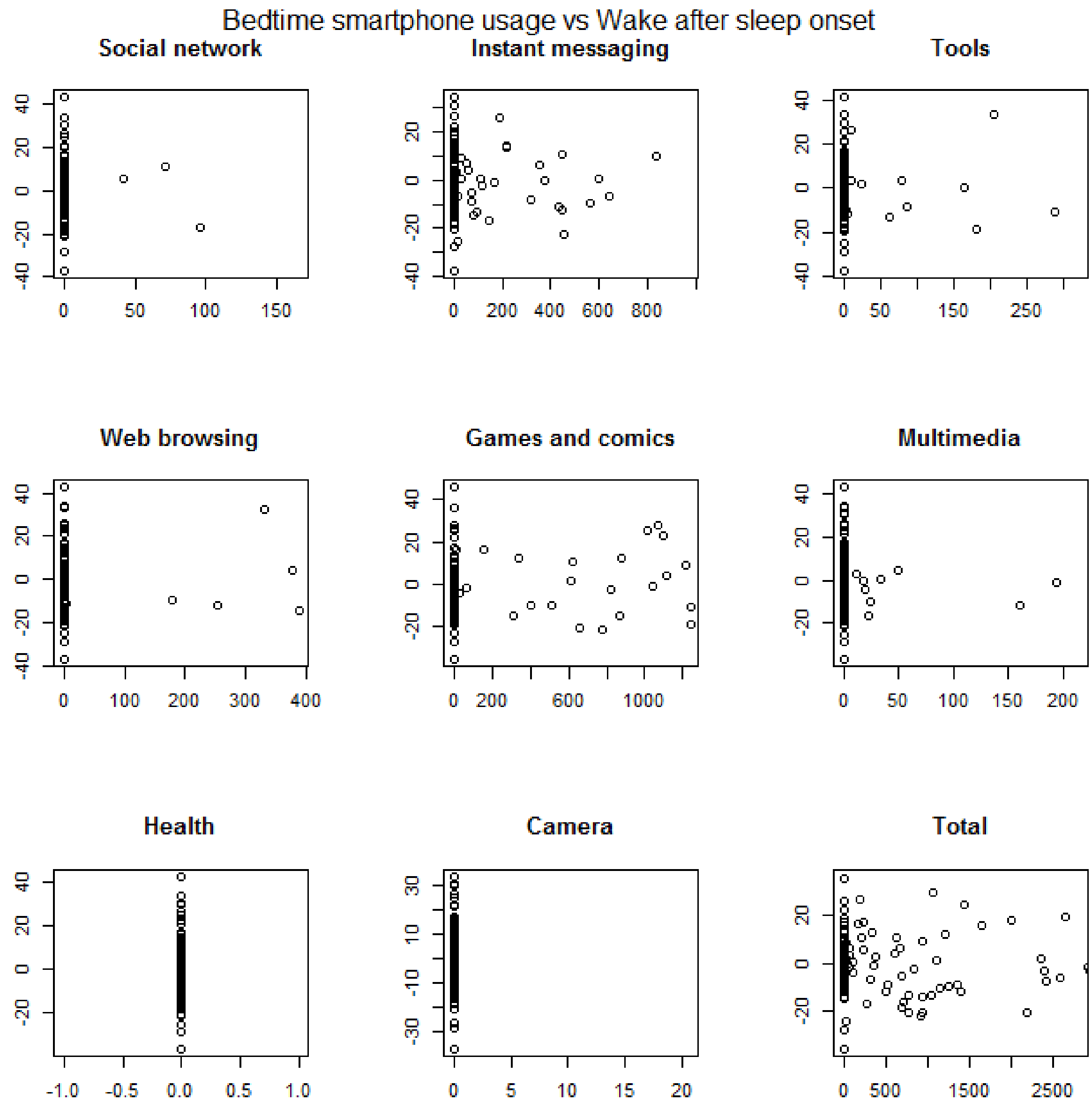

Figure S16. Residual plot of smartphone use during sleep on wake after sleep onset, secondary school students

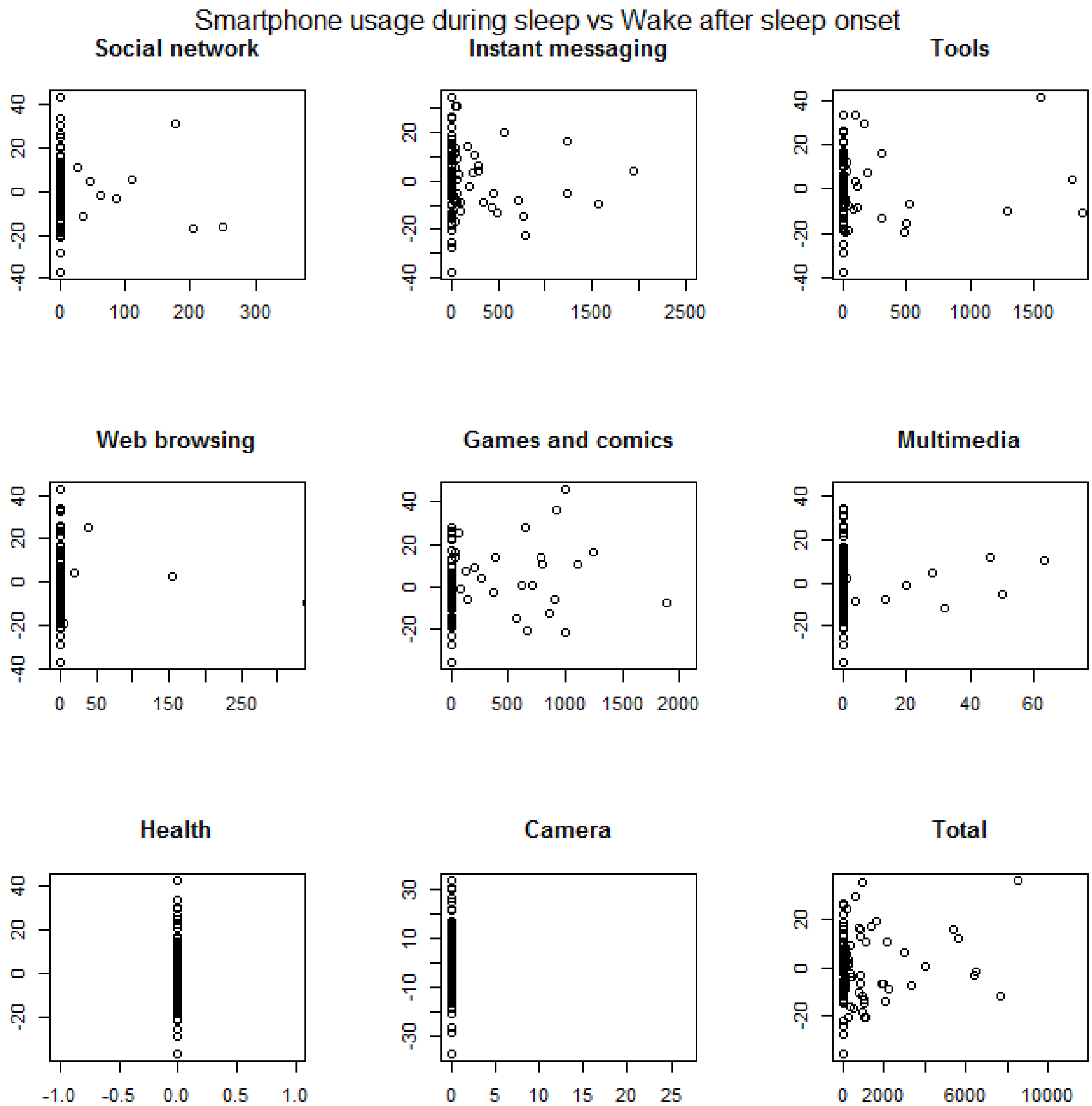

Figure S17. Residual plot of daytime smartphone on number of steps, secondary school students

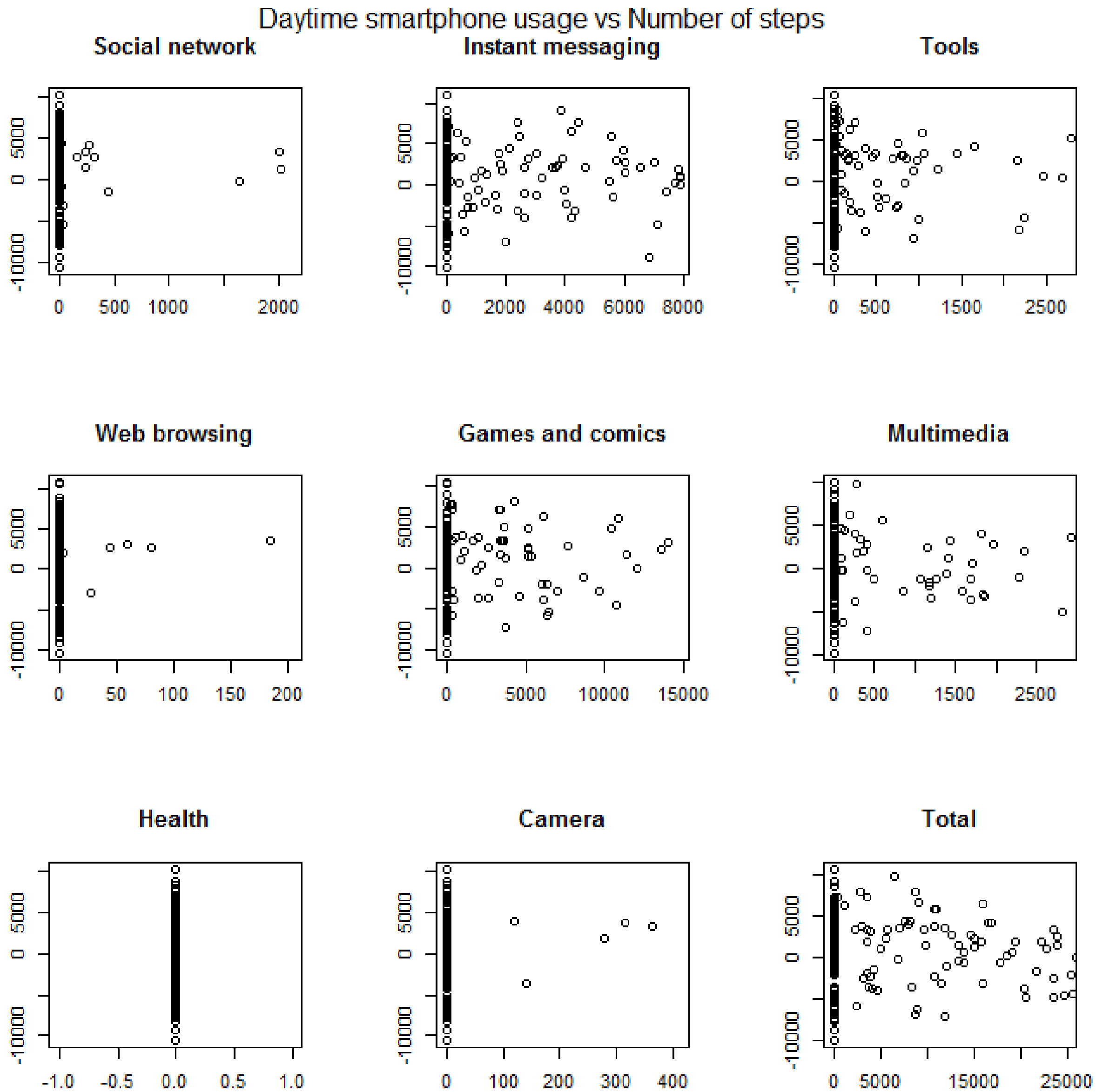

Figure S18. Residual plot of bedtime smartphone on number of steps, secondary school students

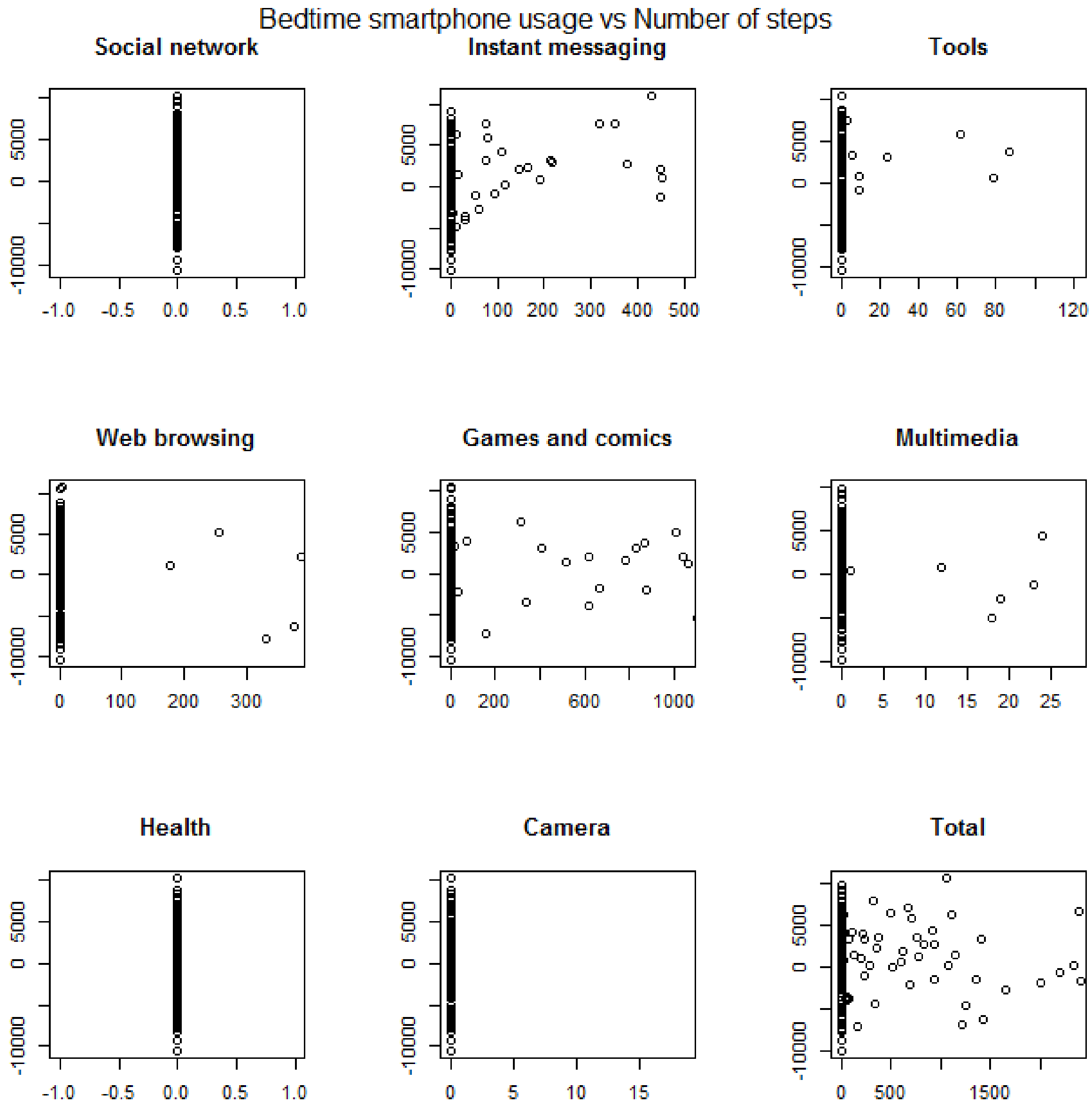

Figure S19. Residual plot of smartphone use during sleep on number of steps, secondary school students

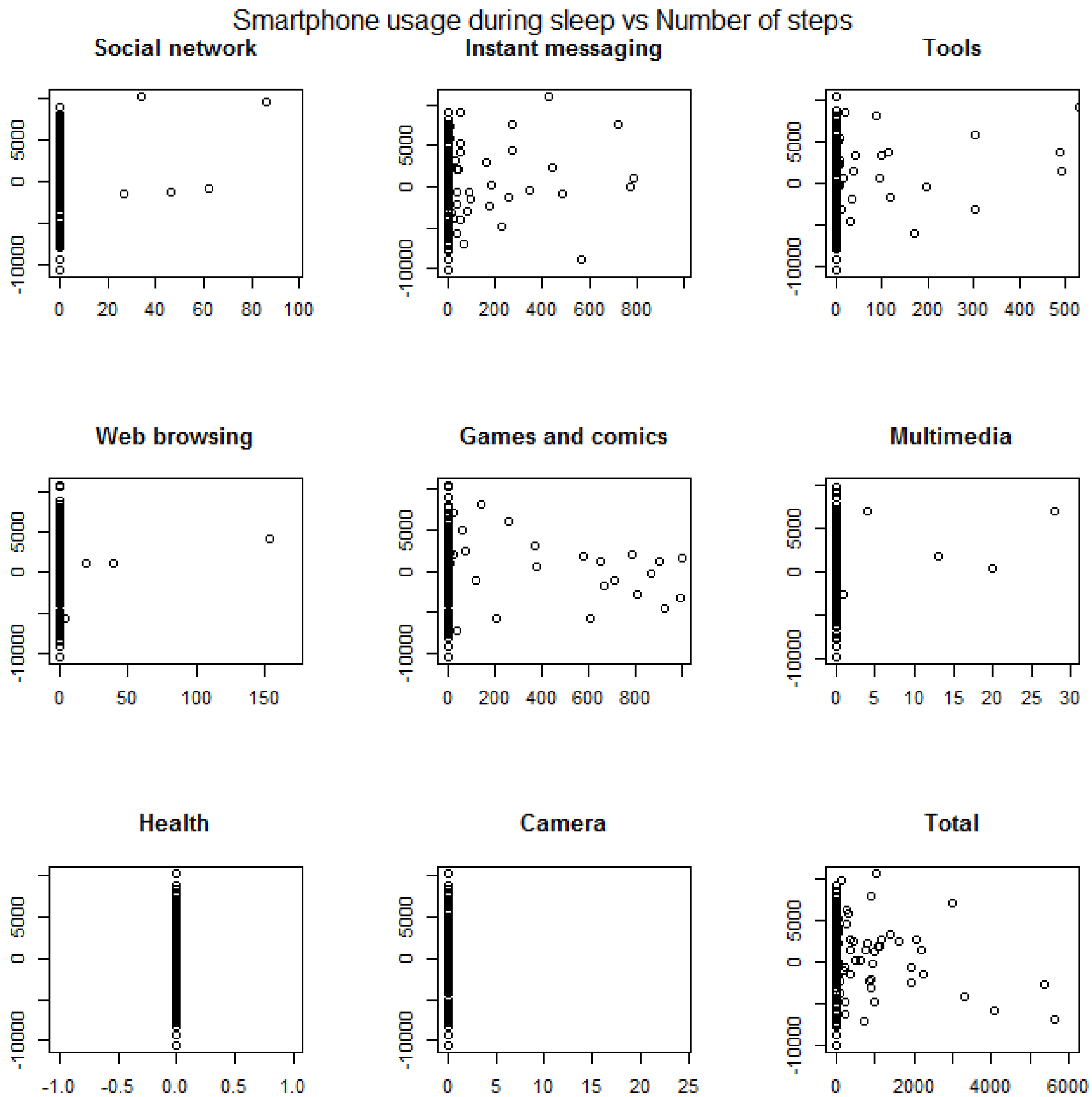

Figure S20. Residual plot of daytime smartphone on time spent on moderate-to-vigorous physical activity, secondary school students

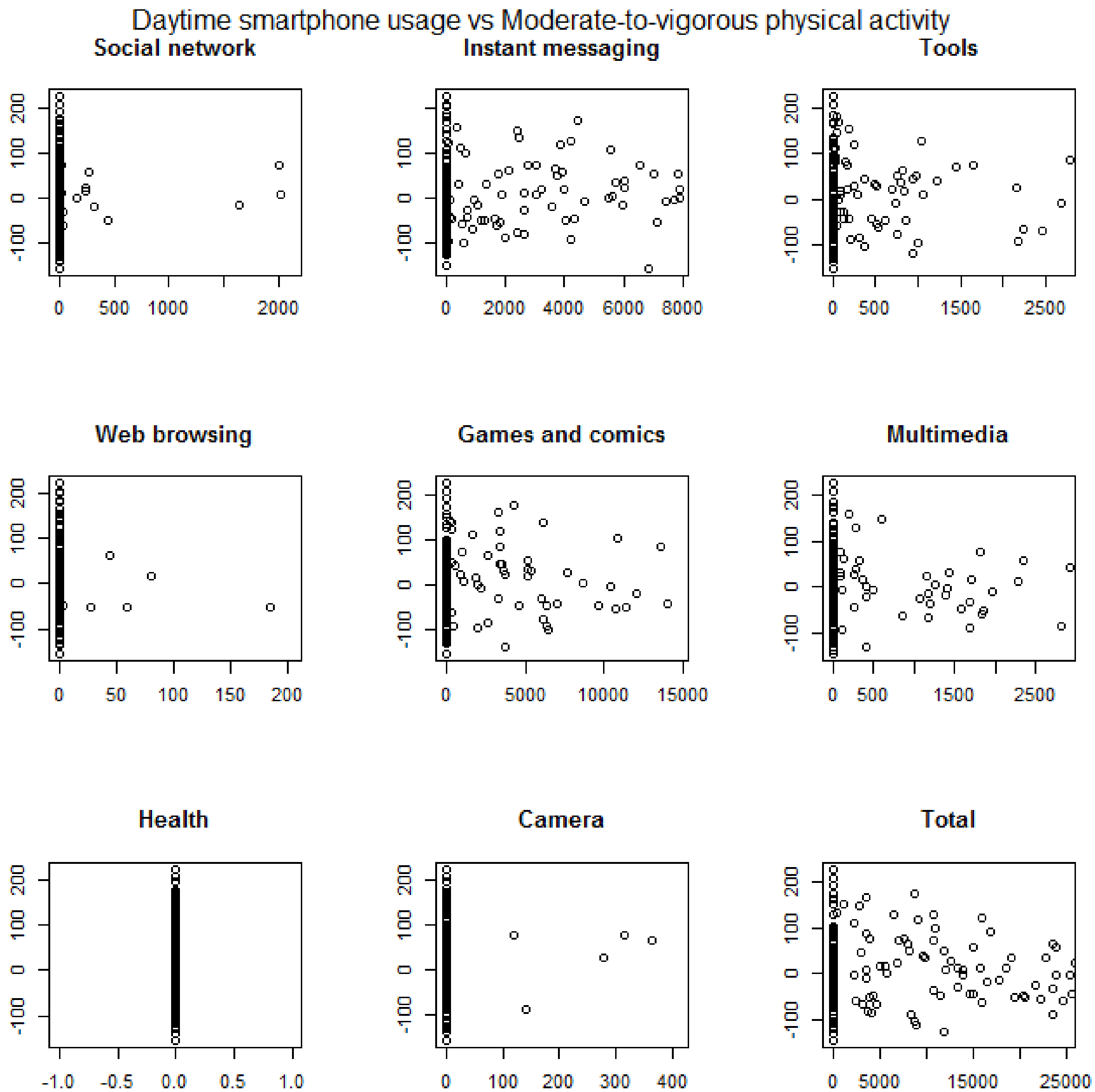

Figure S21. Residual plot of bedtime smartphone on time spent on moderate-to-vigorous physical activity, secondary school students

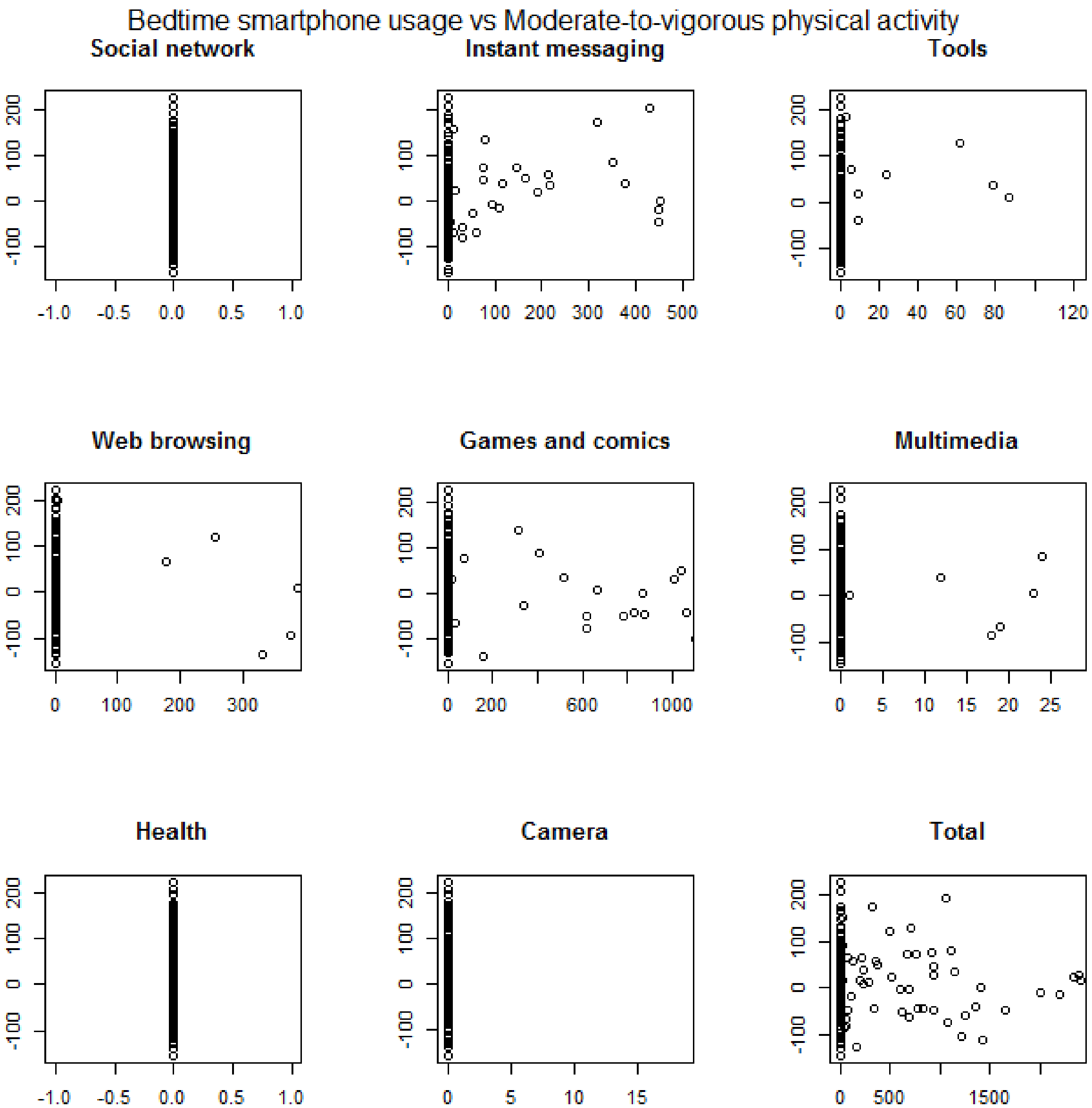

Figure S22. Residual plot of smartphone use during sleep on time spent on moderate-to-vigorous physical activity, secondary school students

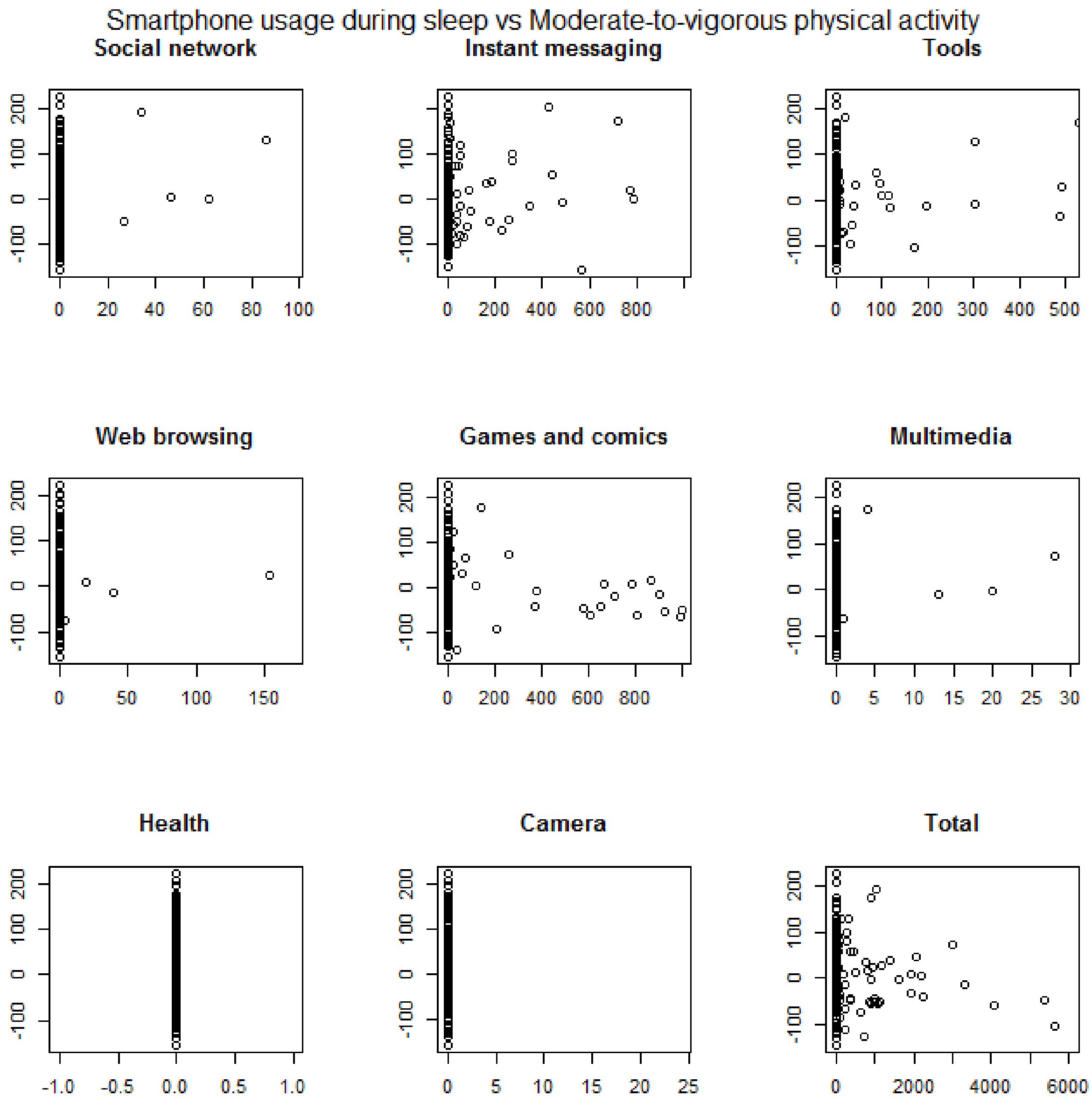

Figure S23. Residual plot of sleep quality on number of steps, secondary school students

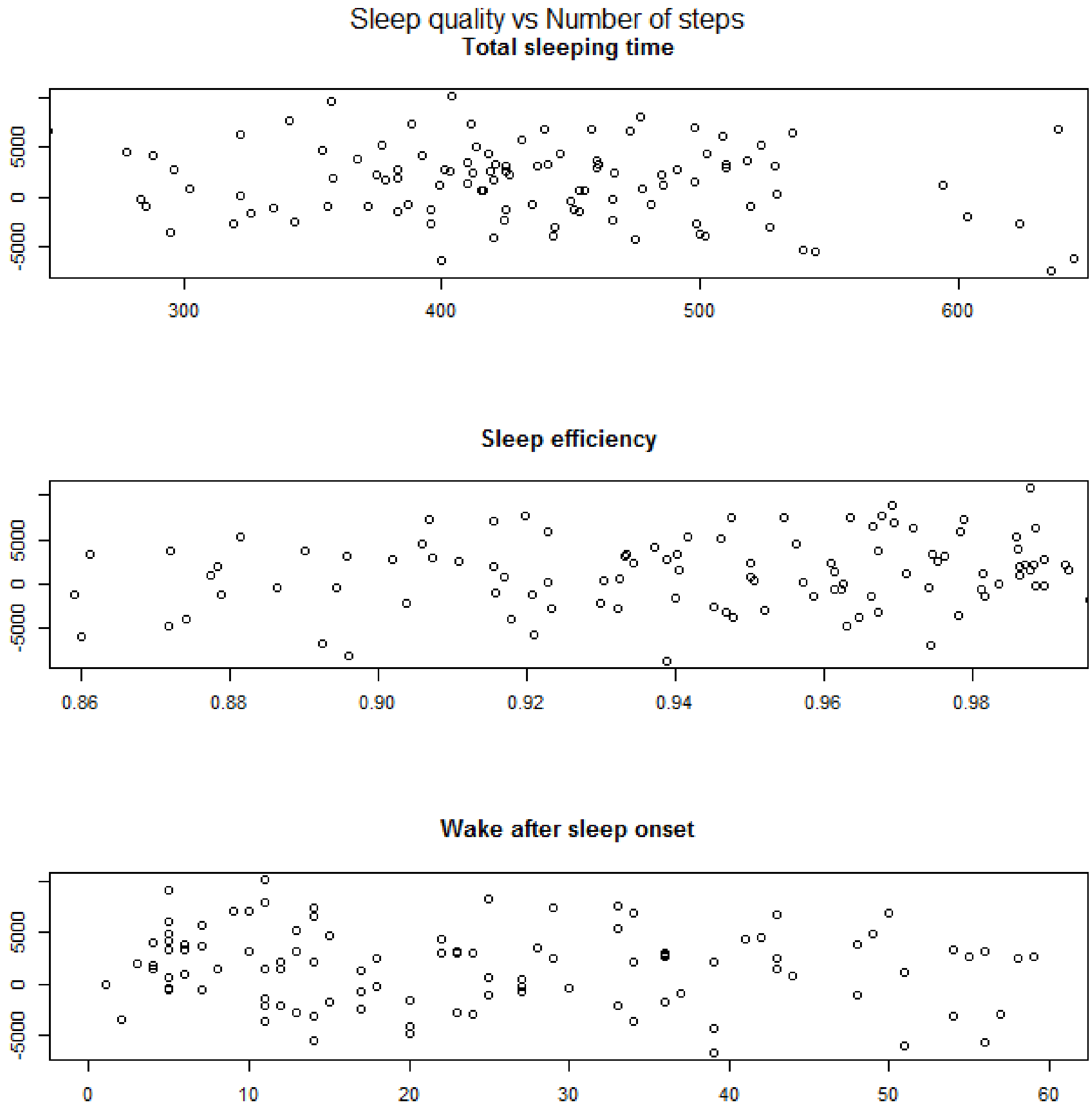

Figure S24. Residual plot of sleep quality on time spent on moderate-to-vigorous physical activity, secondary school students

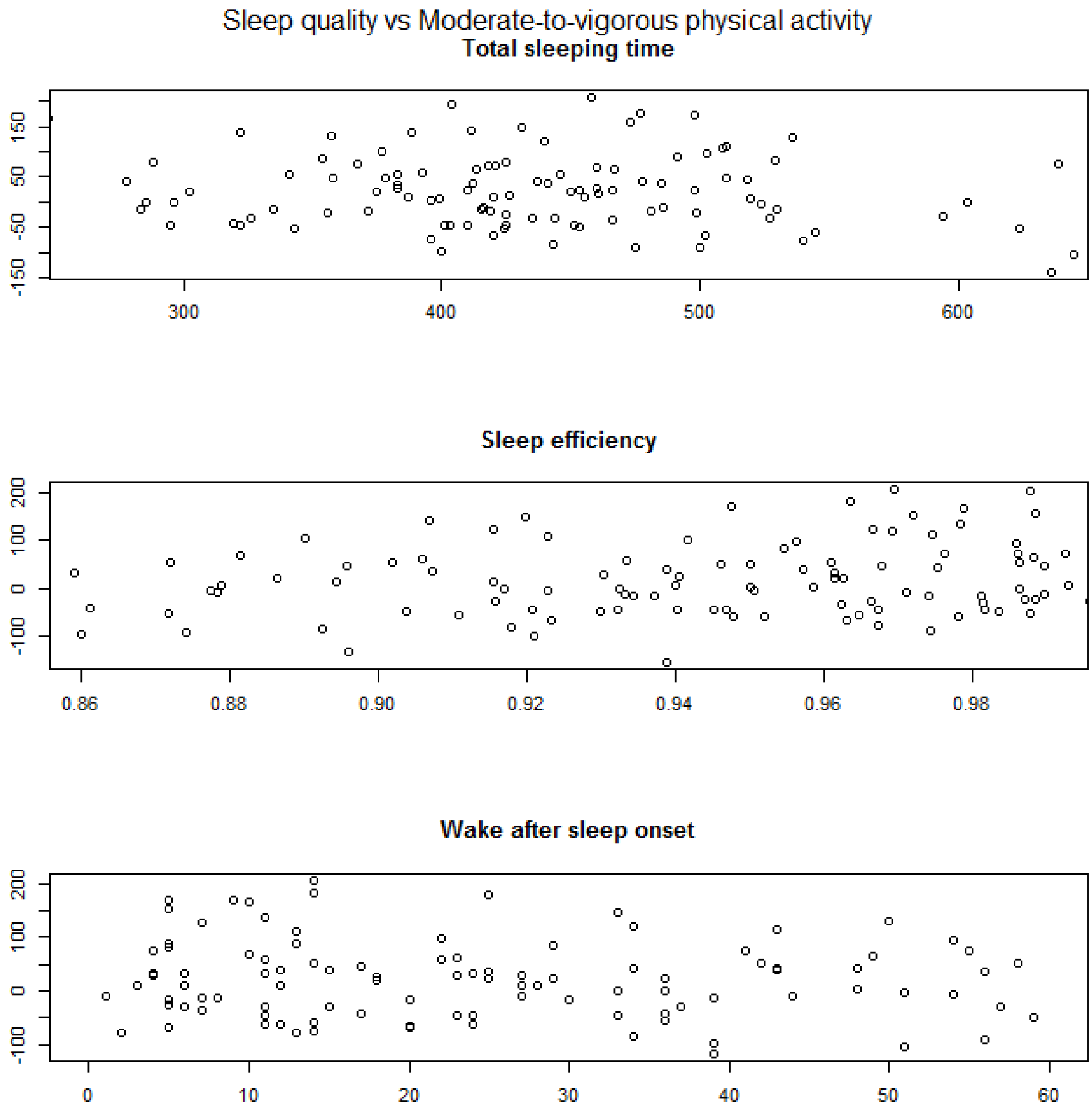

Figure S25. Histogram of the regression residuals of smartphone usage on total sleeping time, university students

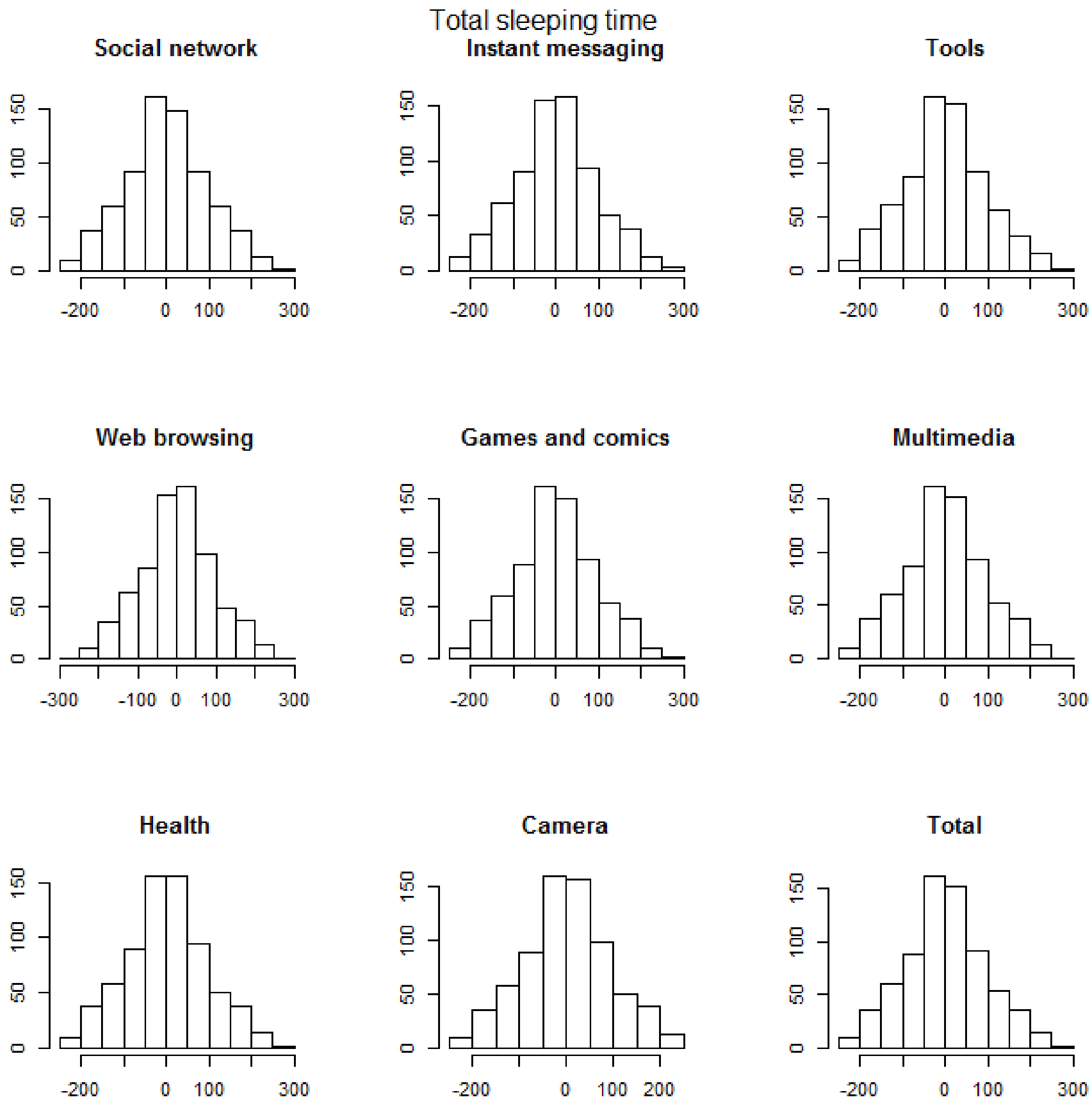

Figure S26. Histogram of the regression residuals of smartphone usage on sleep efficiency, university students

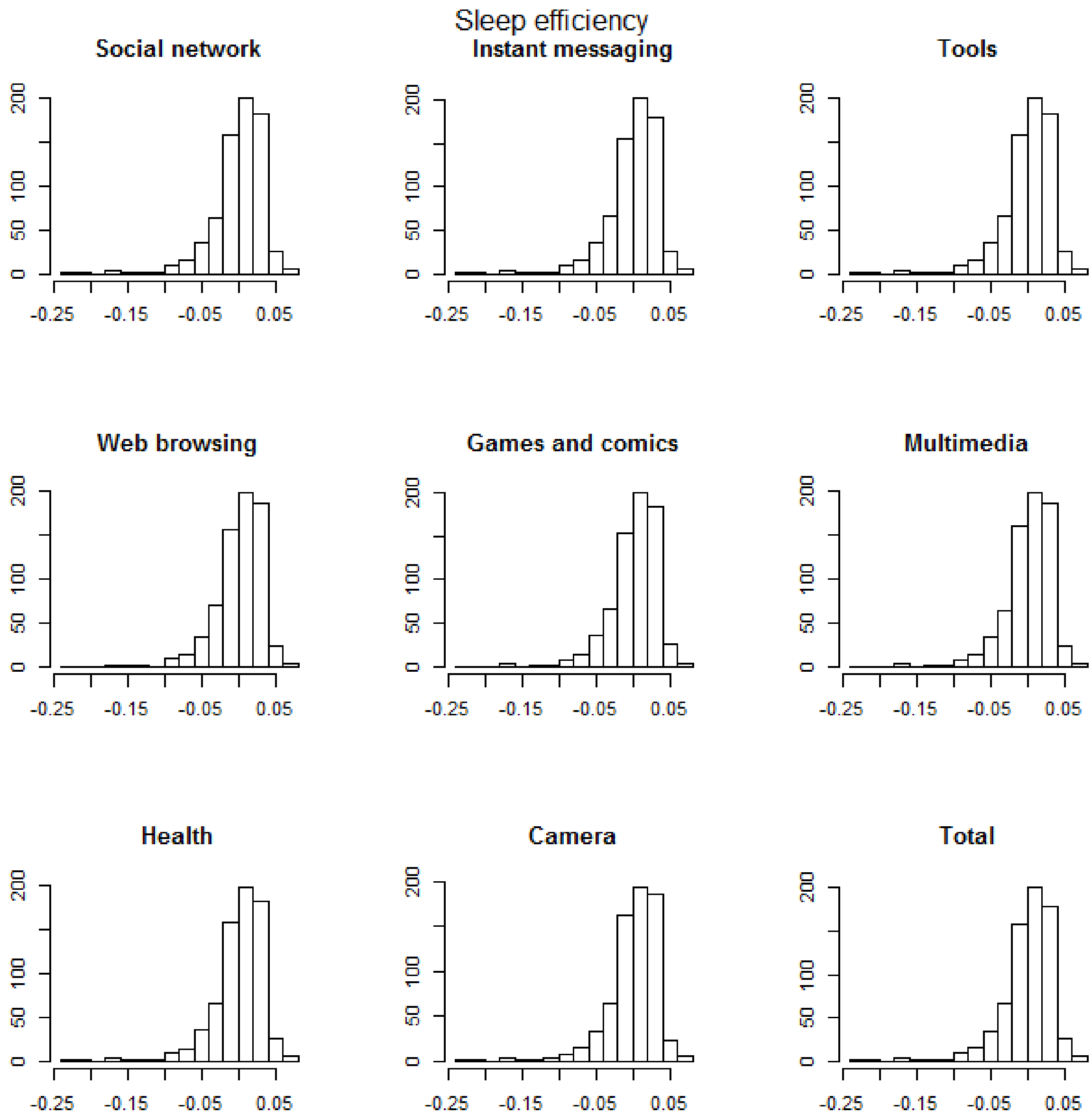

Figure S27. Histogram of the regression residuals of smartphone usage on wake after sleep onset, university students

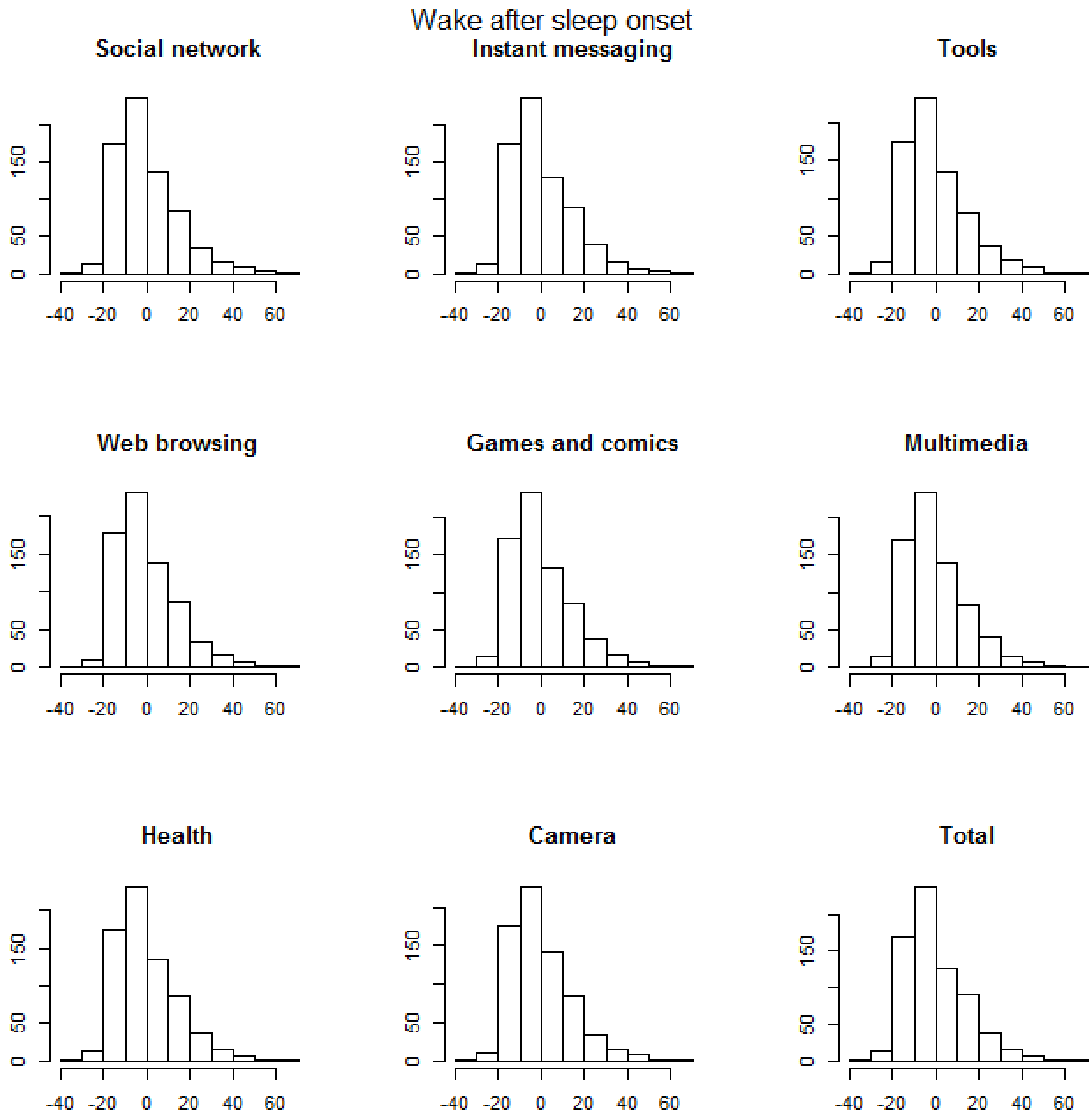

Figure S28. Histogram of the regression residuals of smartphone usage on number of steps, university students

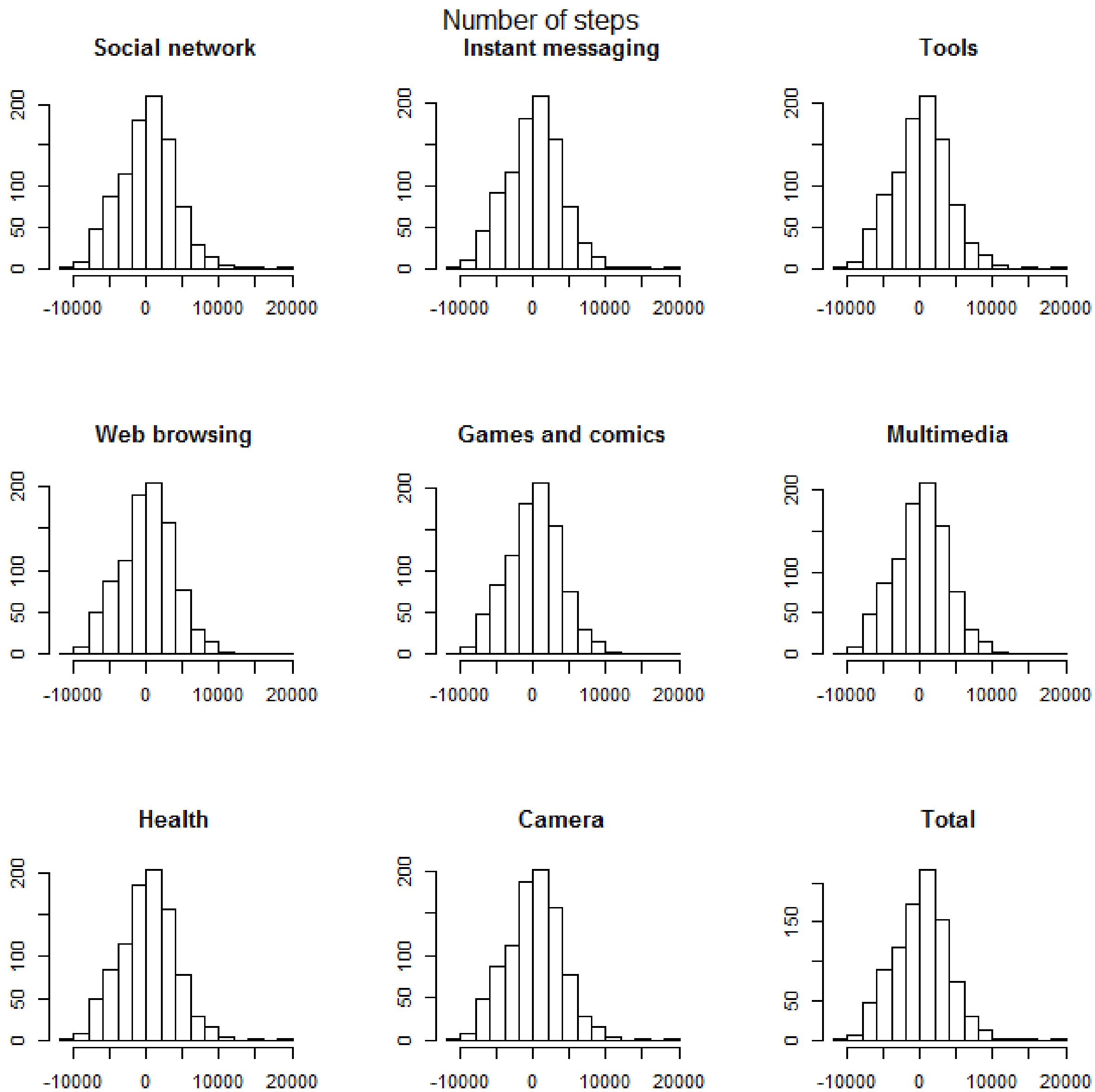

Figure S29. Histogram of the regression residuals of smartphone usage on moderate-to-vigorous physical activity, university students

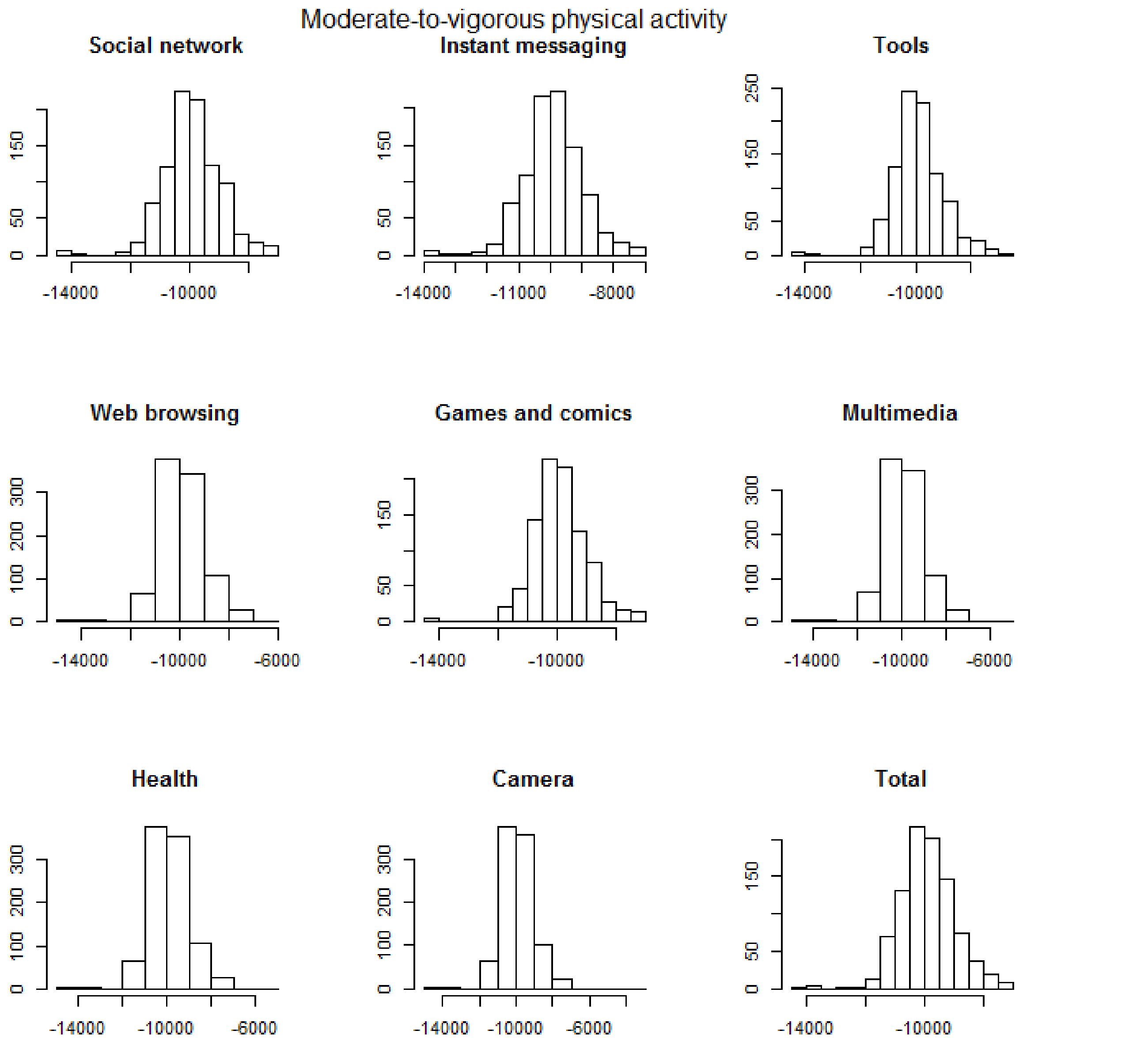

Figure S30. Histogram of the regression residuals of sleep quality on number of steps, university students

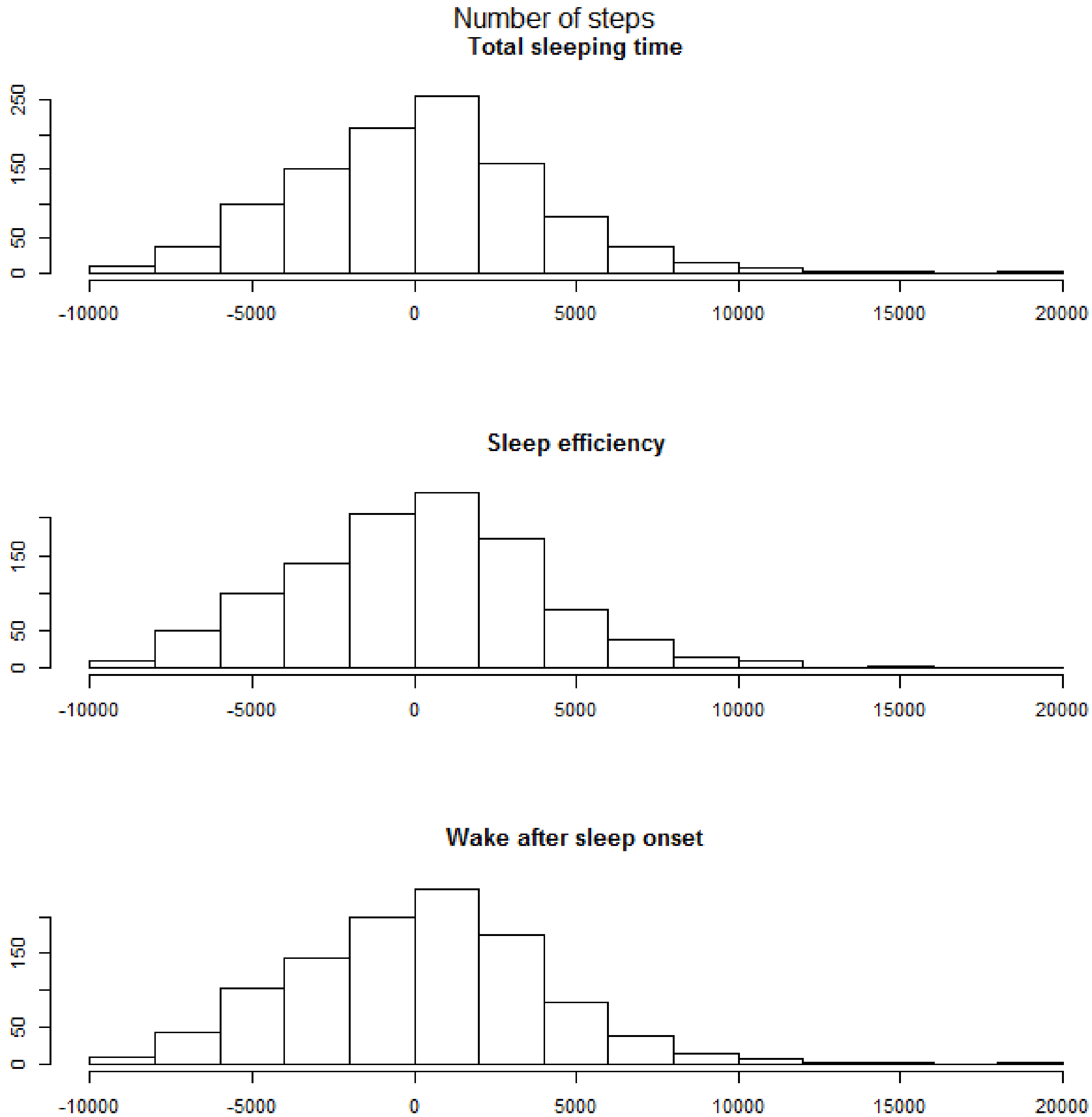

Figure S31. Histogram of the regression residuals of sleep quality on moderate-to-vigorous physical activity, university students

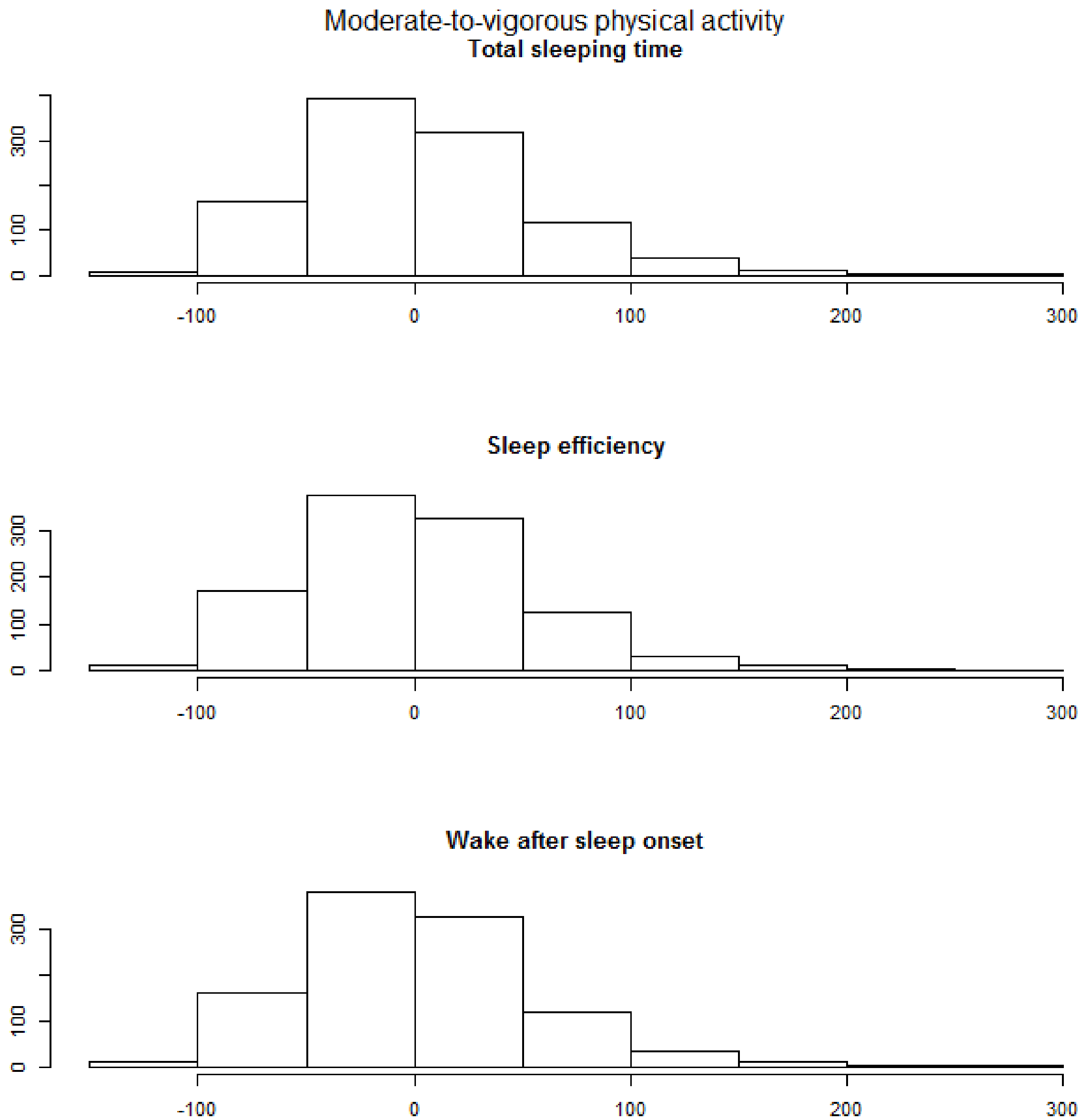

Figure S32. Residual plot of daytime smartphone use on total sleeping time, university students

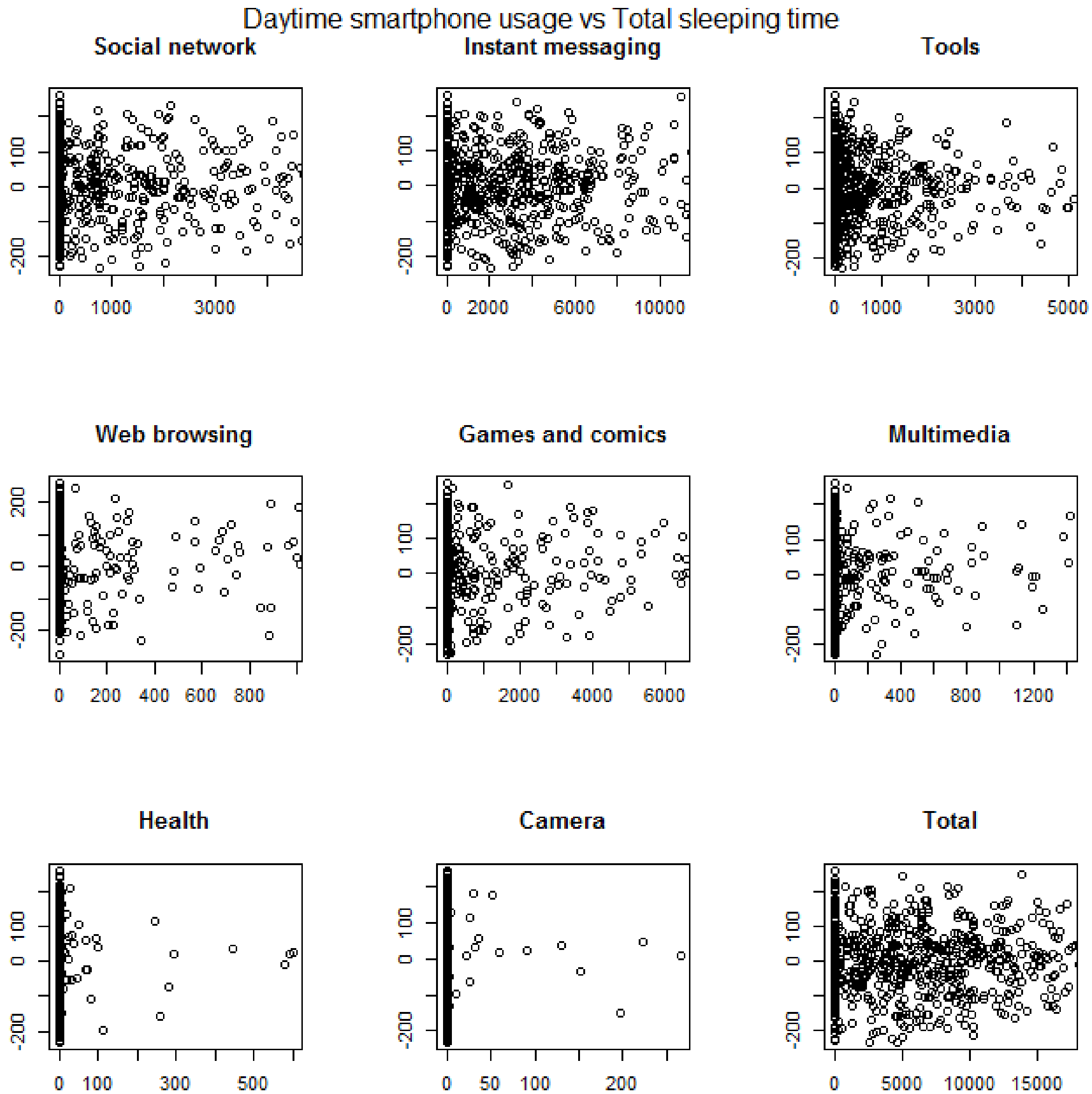

Figure S33. Residual plot of bedtime smartphone use on total sleeping time, university students

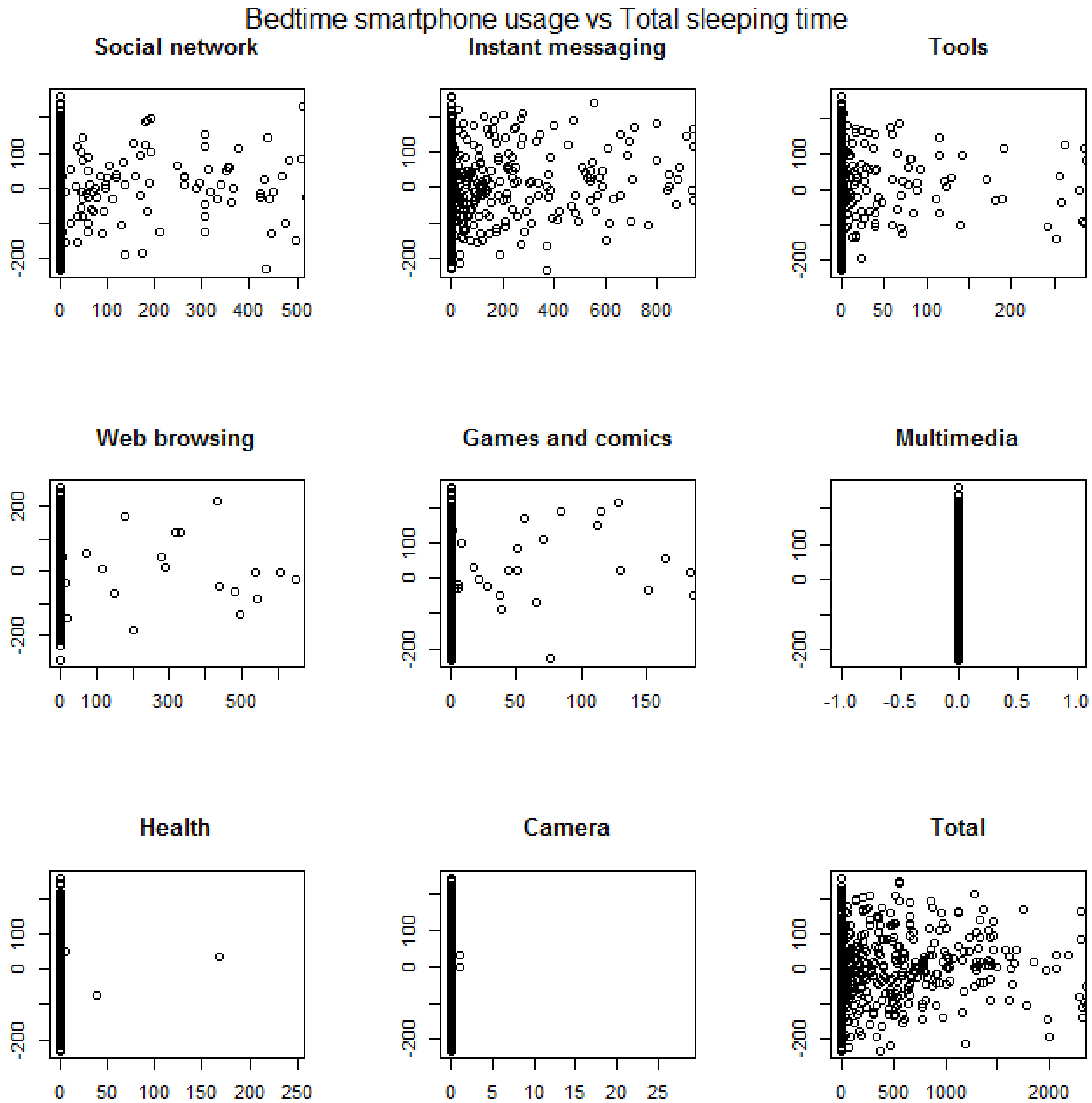

Figure S34. Residual plot of smartphone use during sleep on total sleeping time, university students

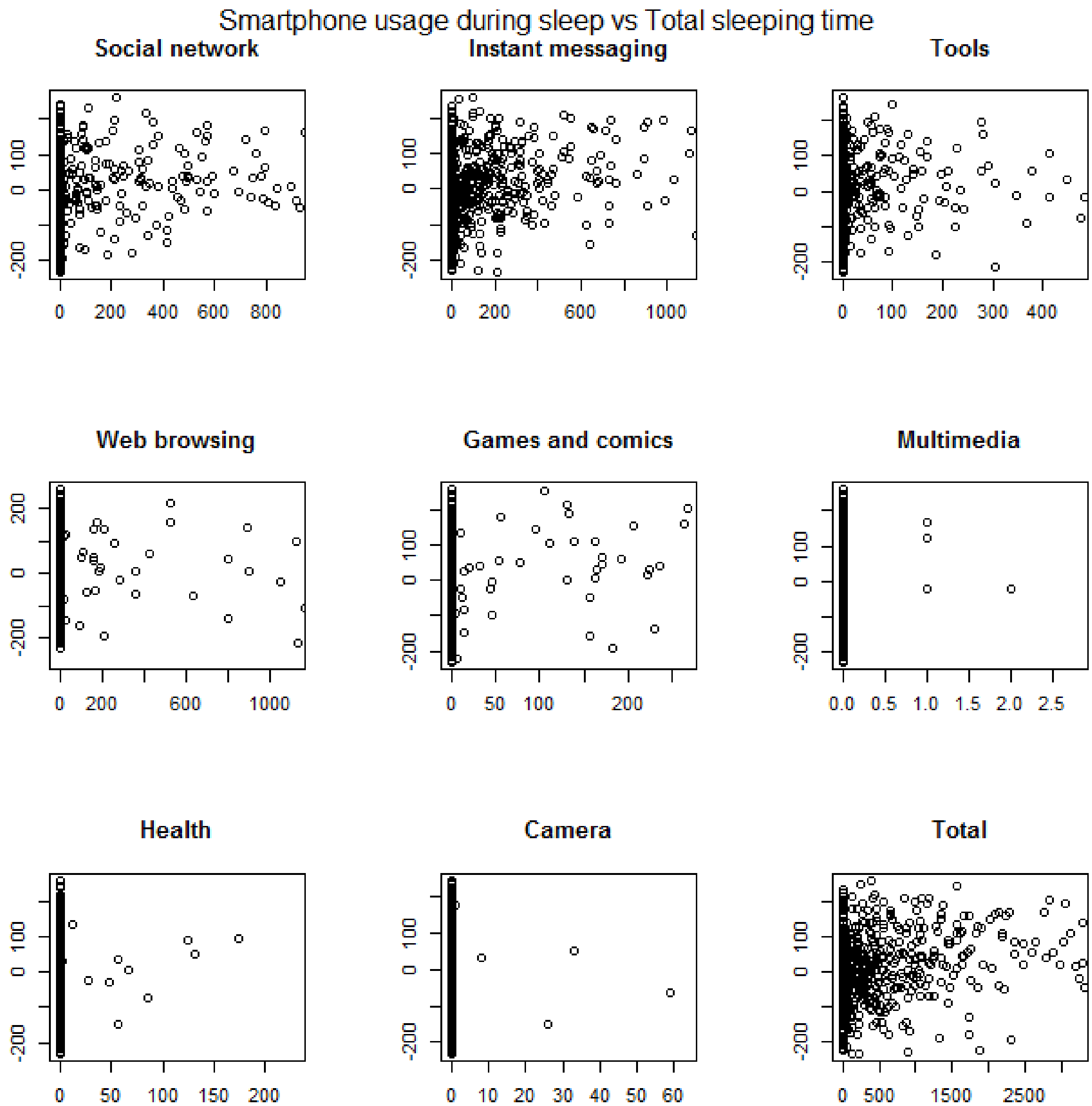

Figure S35. Residual plot of daytime smartphone use on sleep efficiency, university students

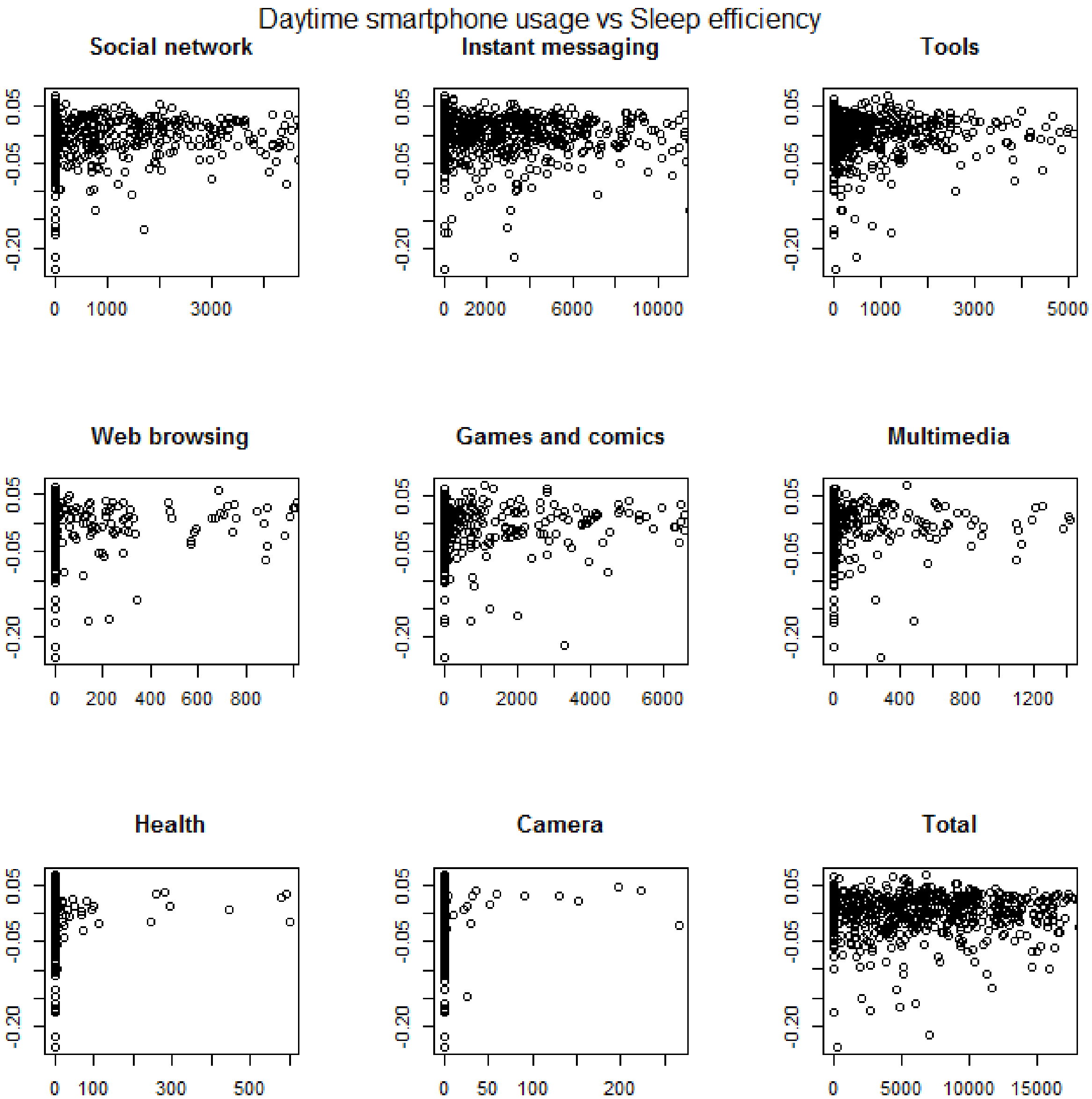

Figure S36. Residual plot of bedtime smartphone use on sleep efficiency, university students

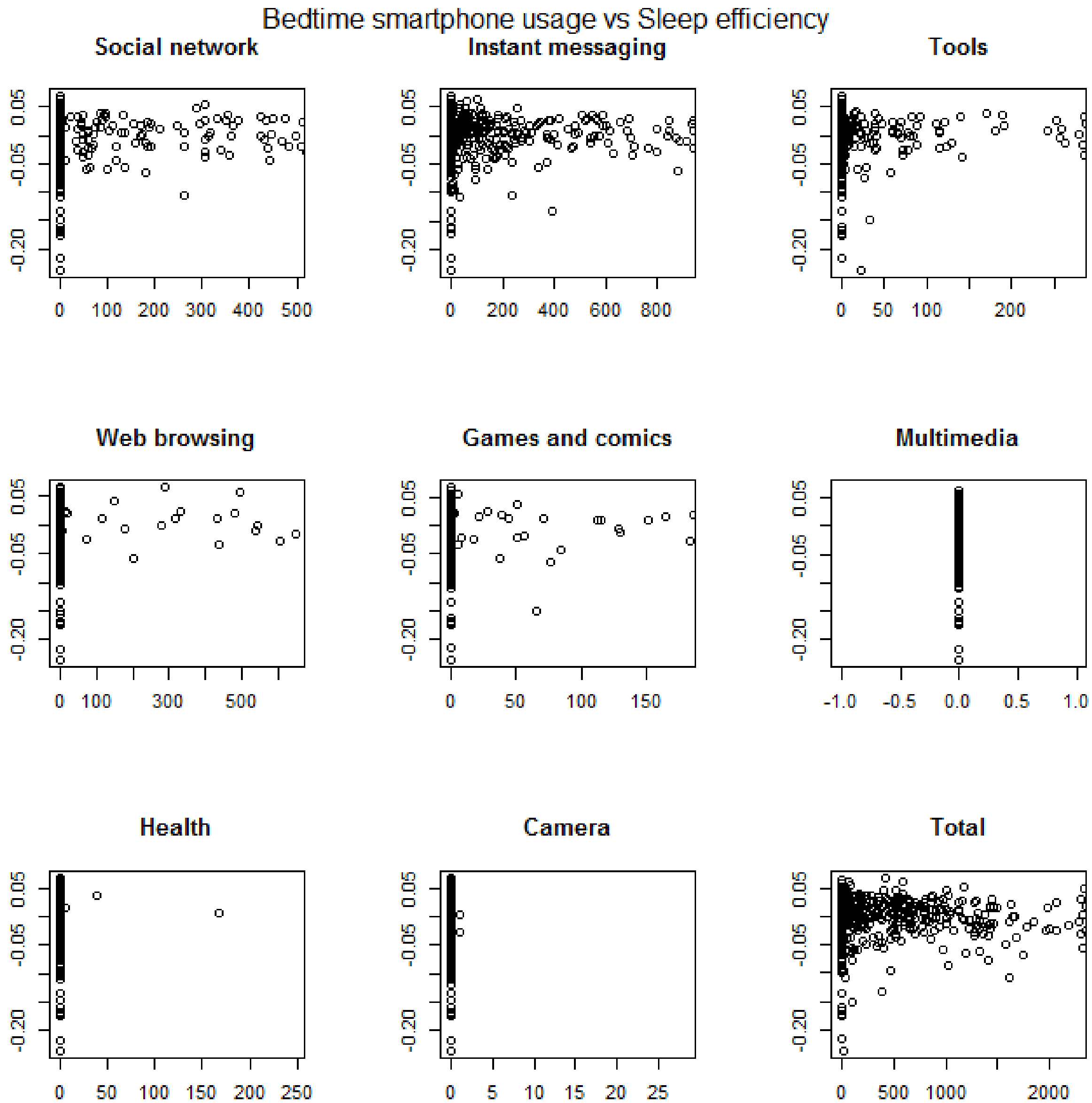

Figure S37. Residual plot of smartphone use during sleep on sleep efficiency, university students

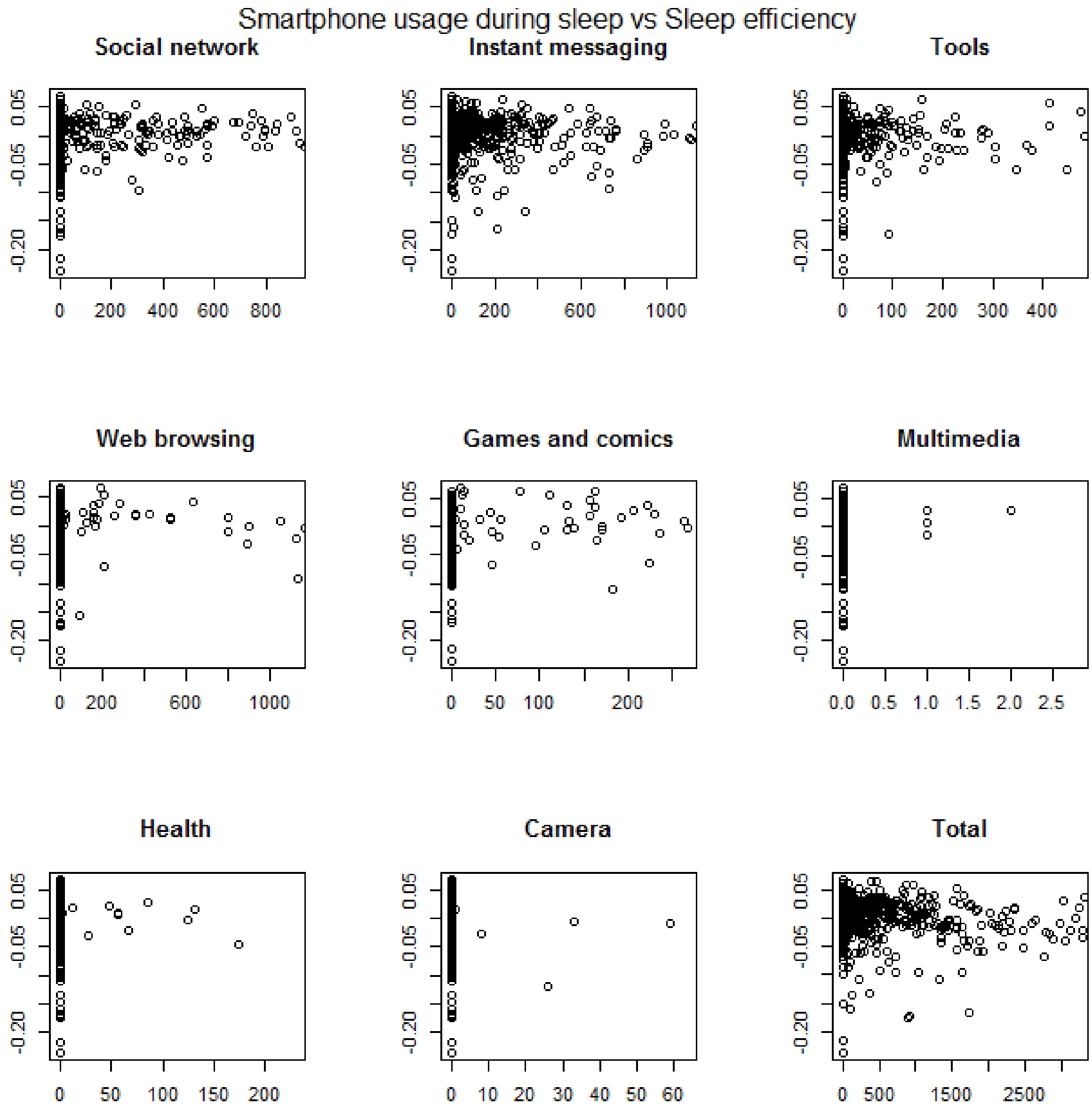

Figure S38. Residual plot of daytime smartphone use on wake after sleep onset, university students

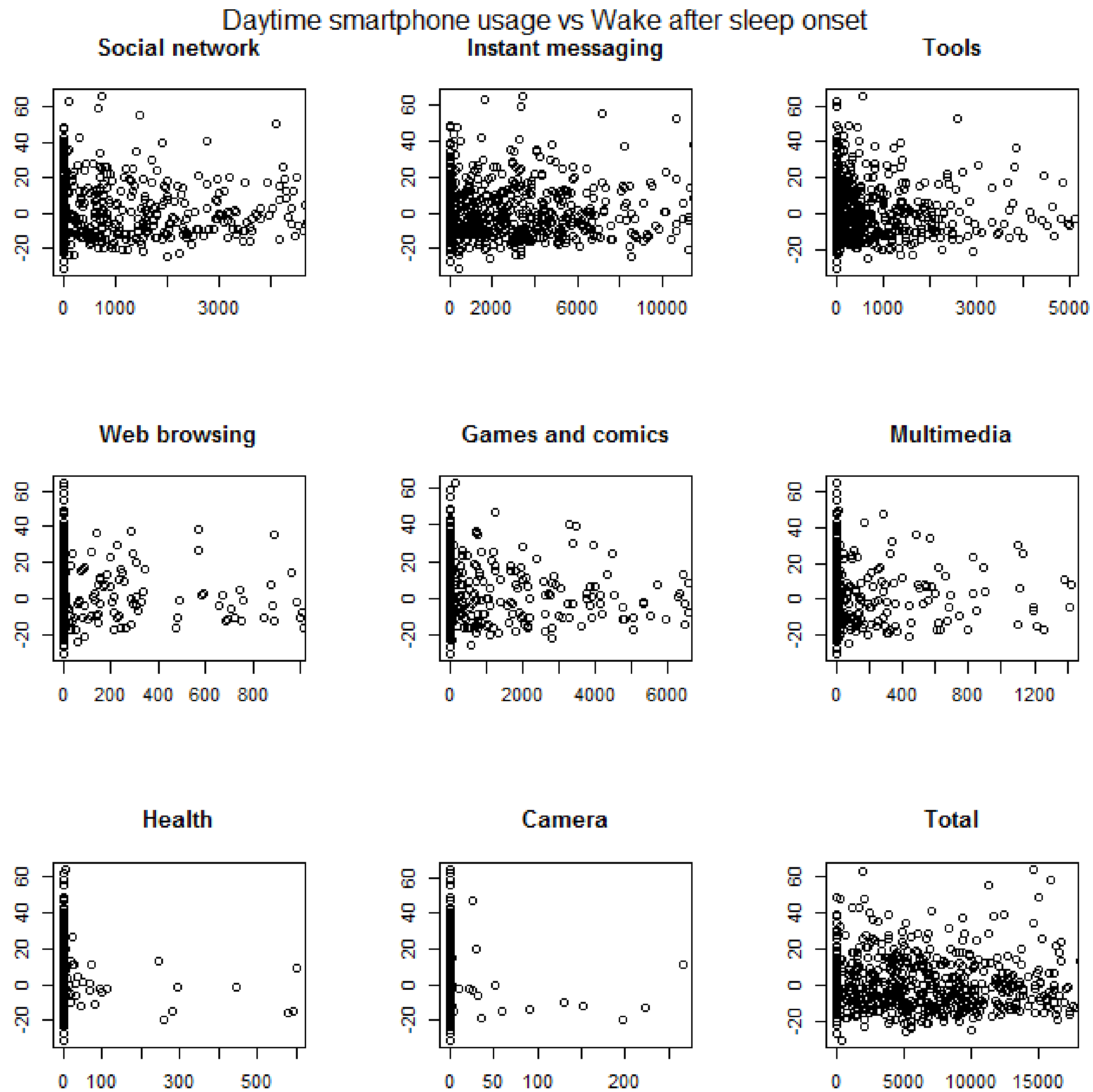

Figure S39. Residual plot of bedtime smartphone use on wake after sleep onset, university students

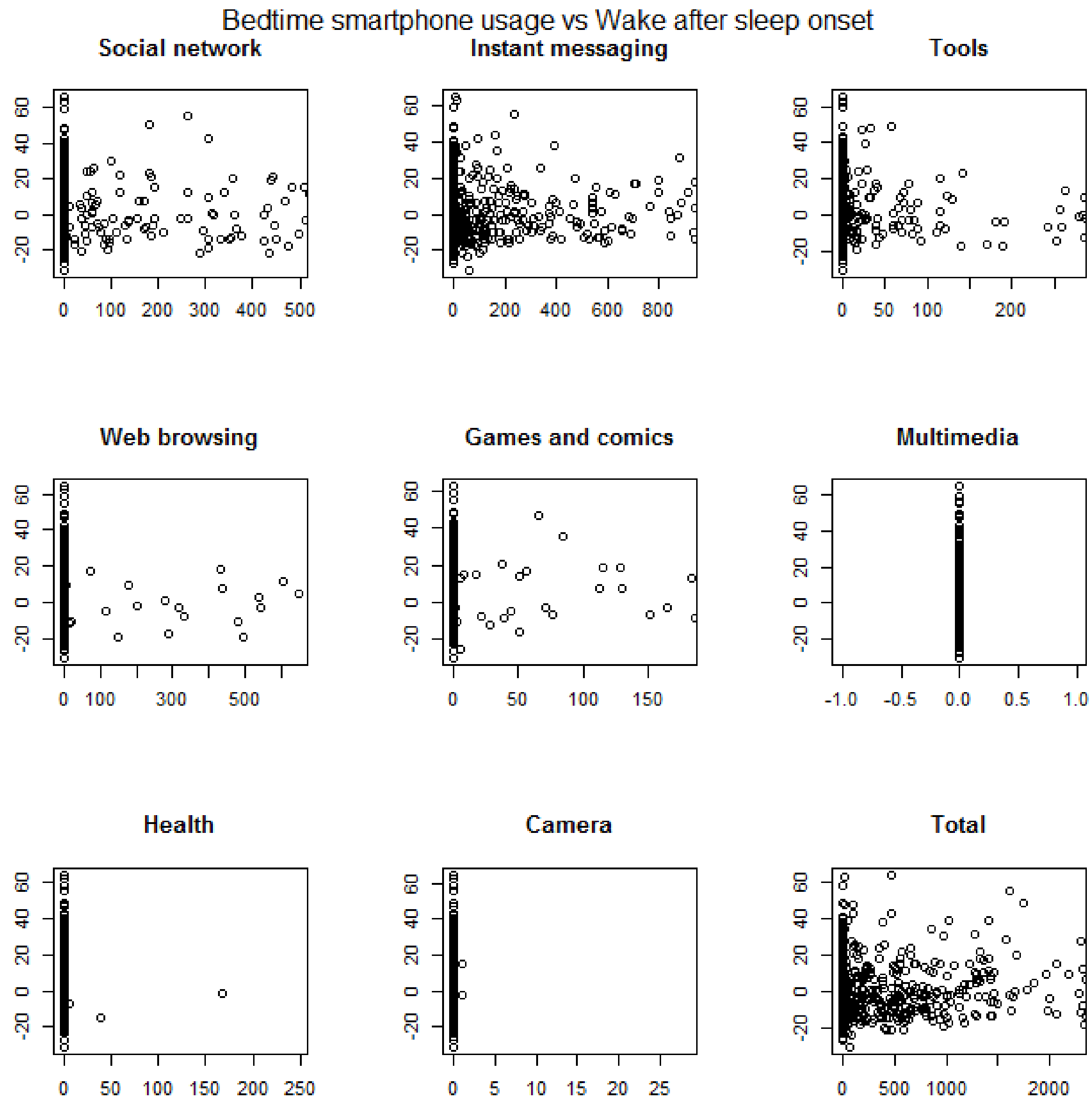

Figure S40. Residual plot of smartphone use during sleep on wake after sleep onset, university students

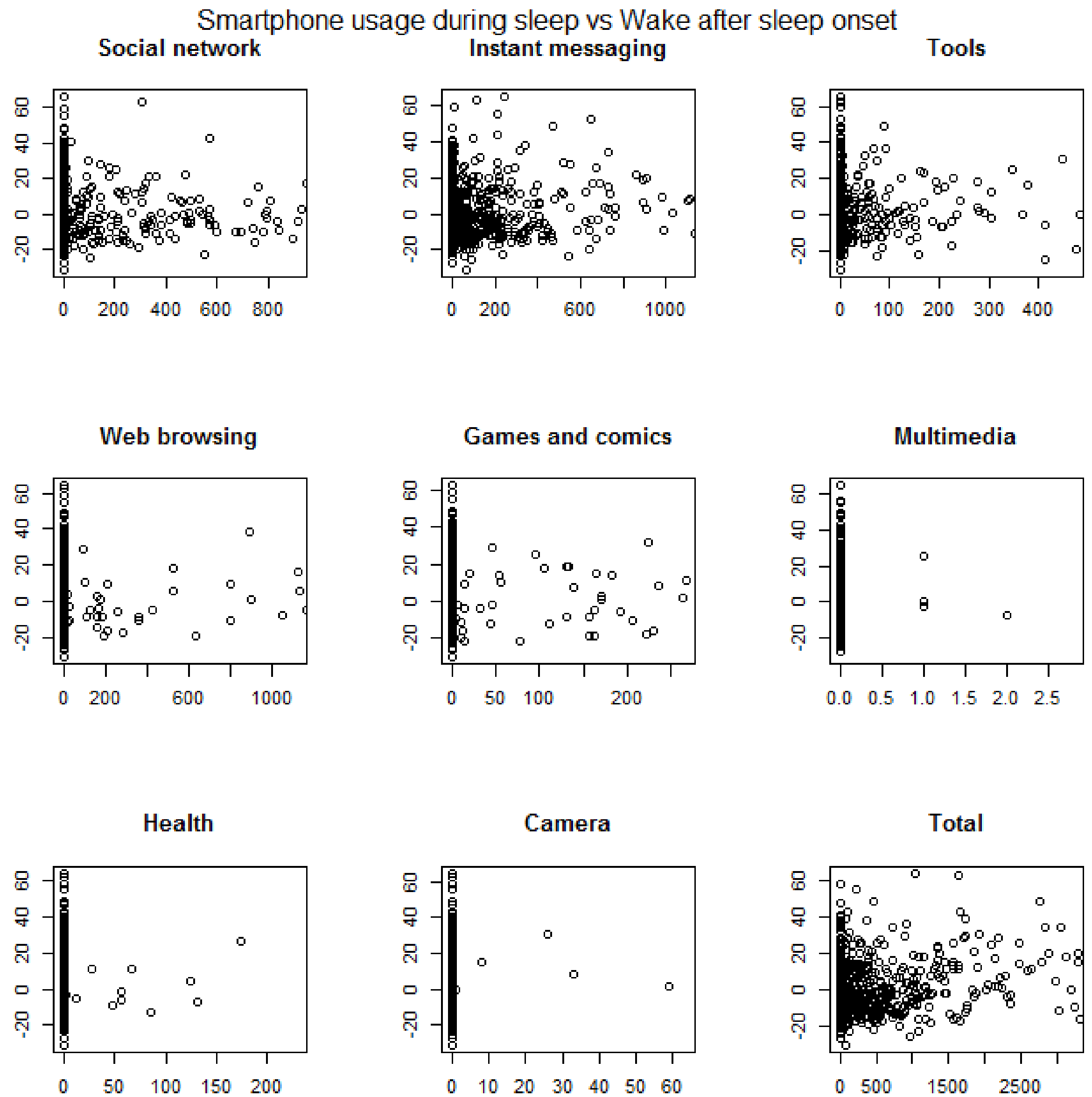

Figure S41. Residual plot of daytime smartphone on number of steps, university students

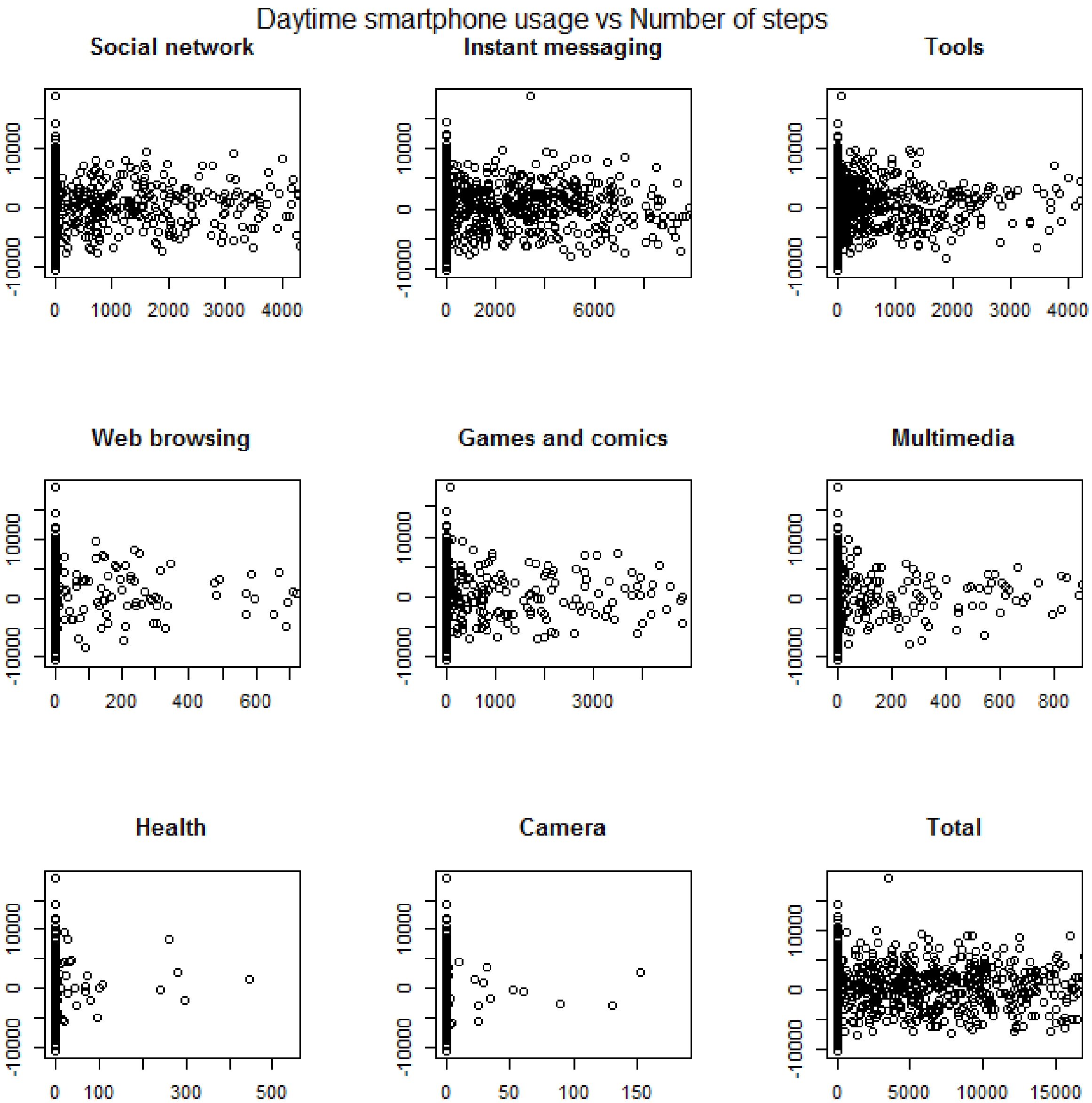

Figure S42. Residual plot of bedtime smartphone on number of steps, university students

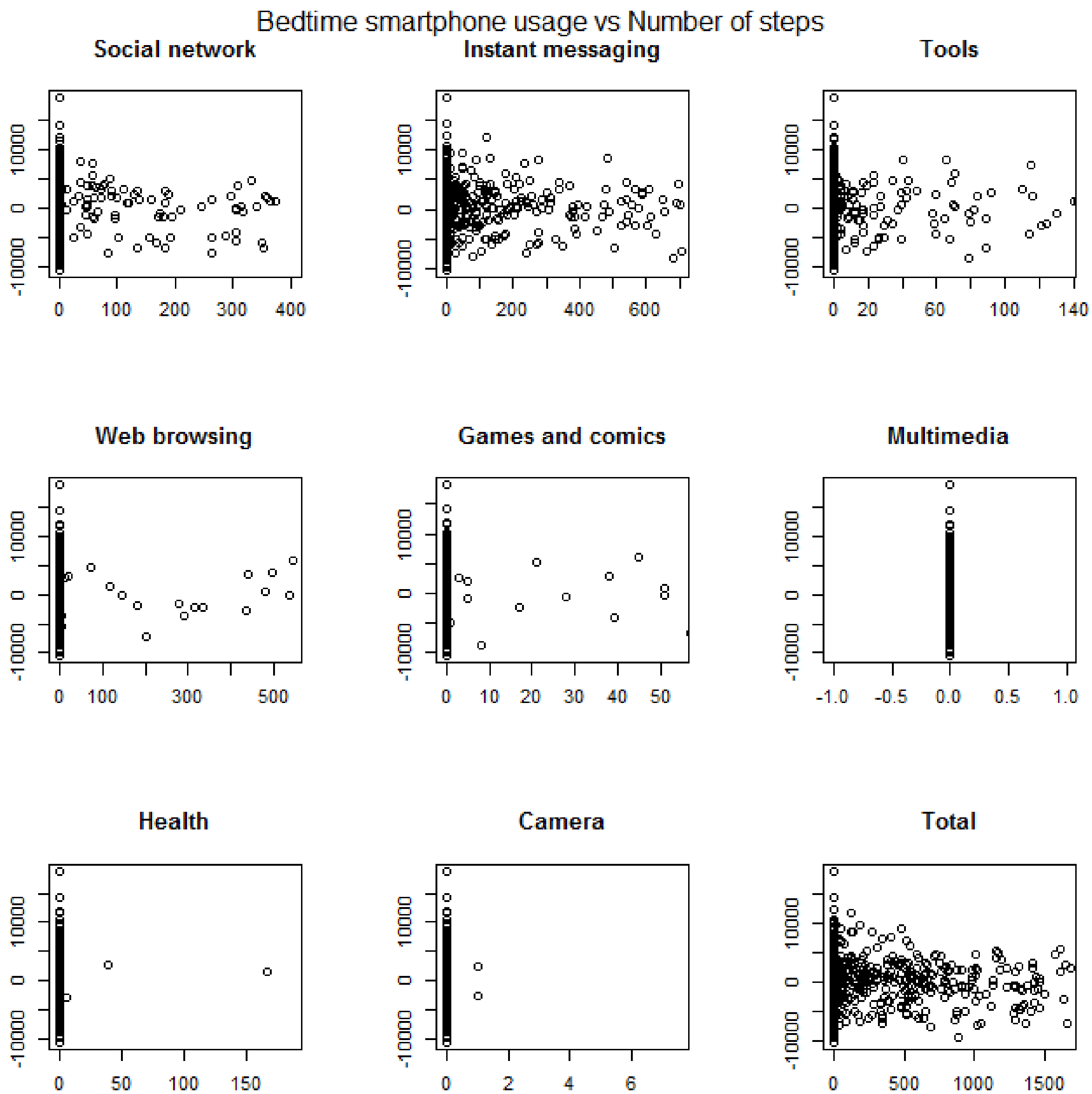

Figure S43. Residual plot of smartphone use during sleep on number of steps, university students

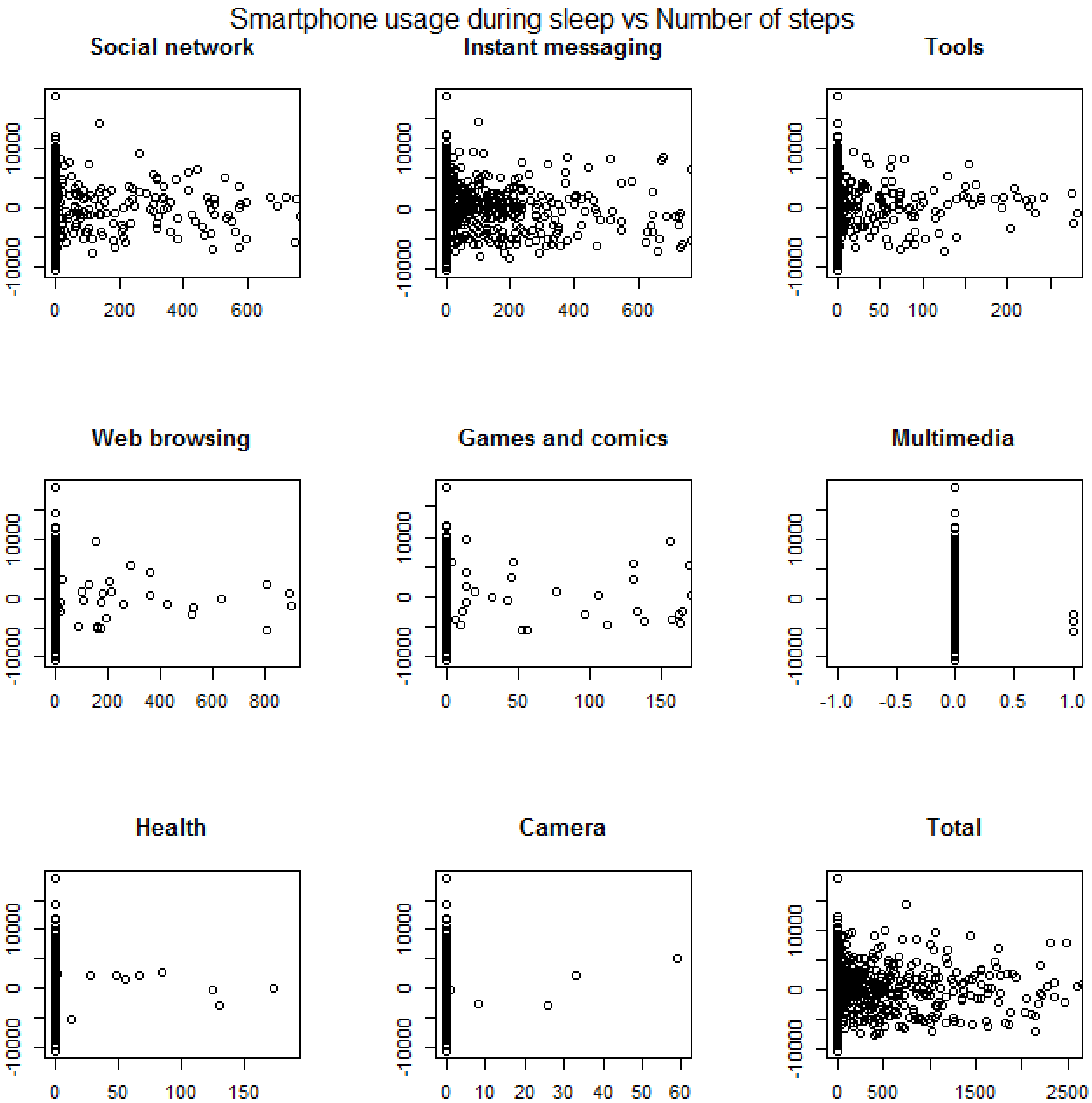

Figure S44. Residual plot of daytime smartphone on time spent on moderate-to-vigorous physical activity, university students

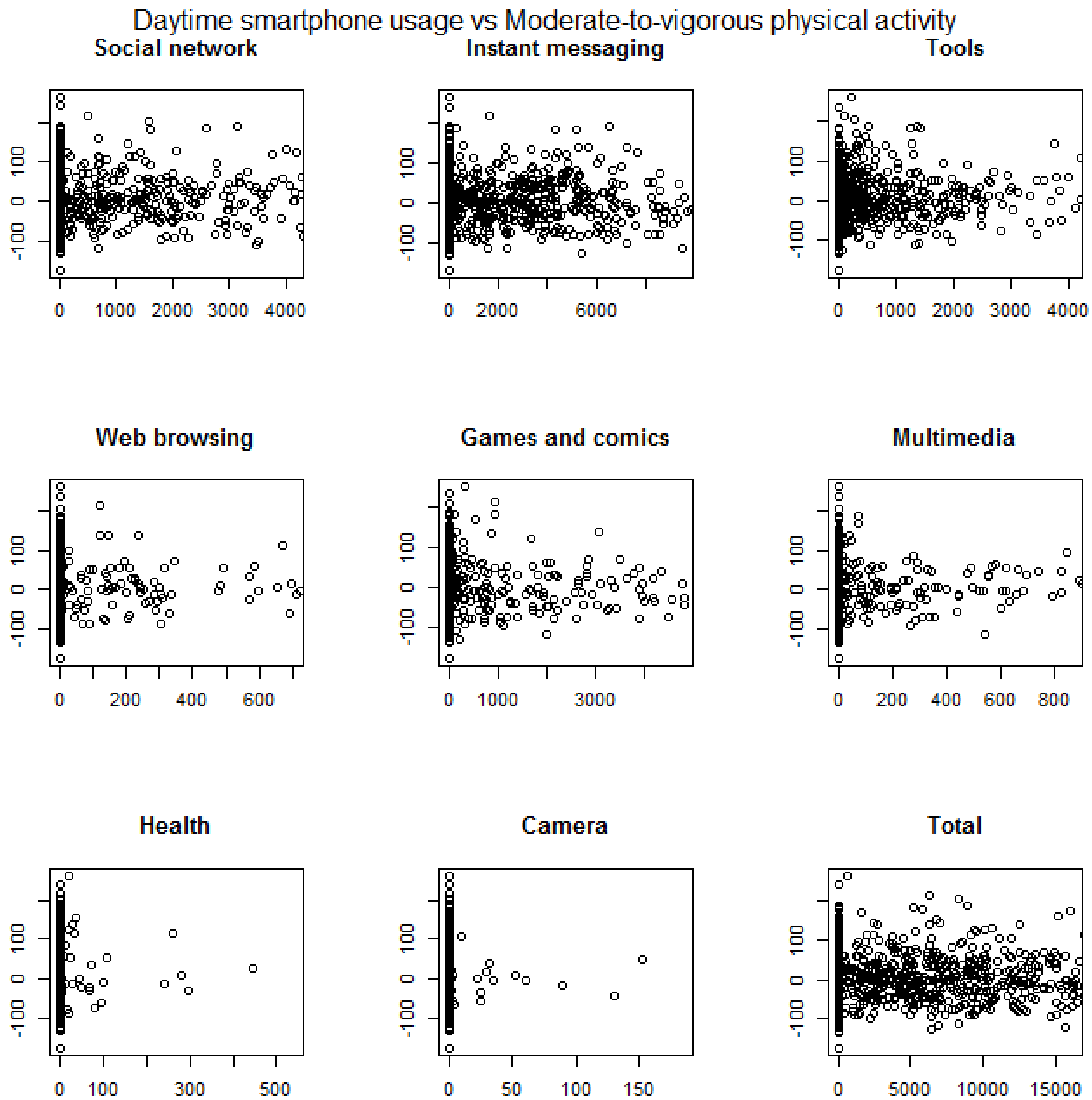

Figure S45. Residual plot of bedtime smartphone on time spent on moderate-to-vigorous physical activity, university students

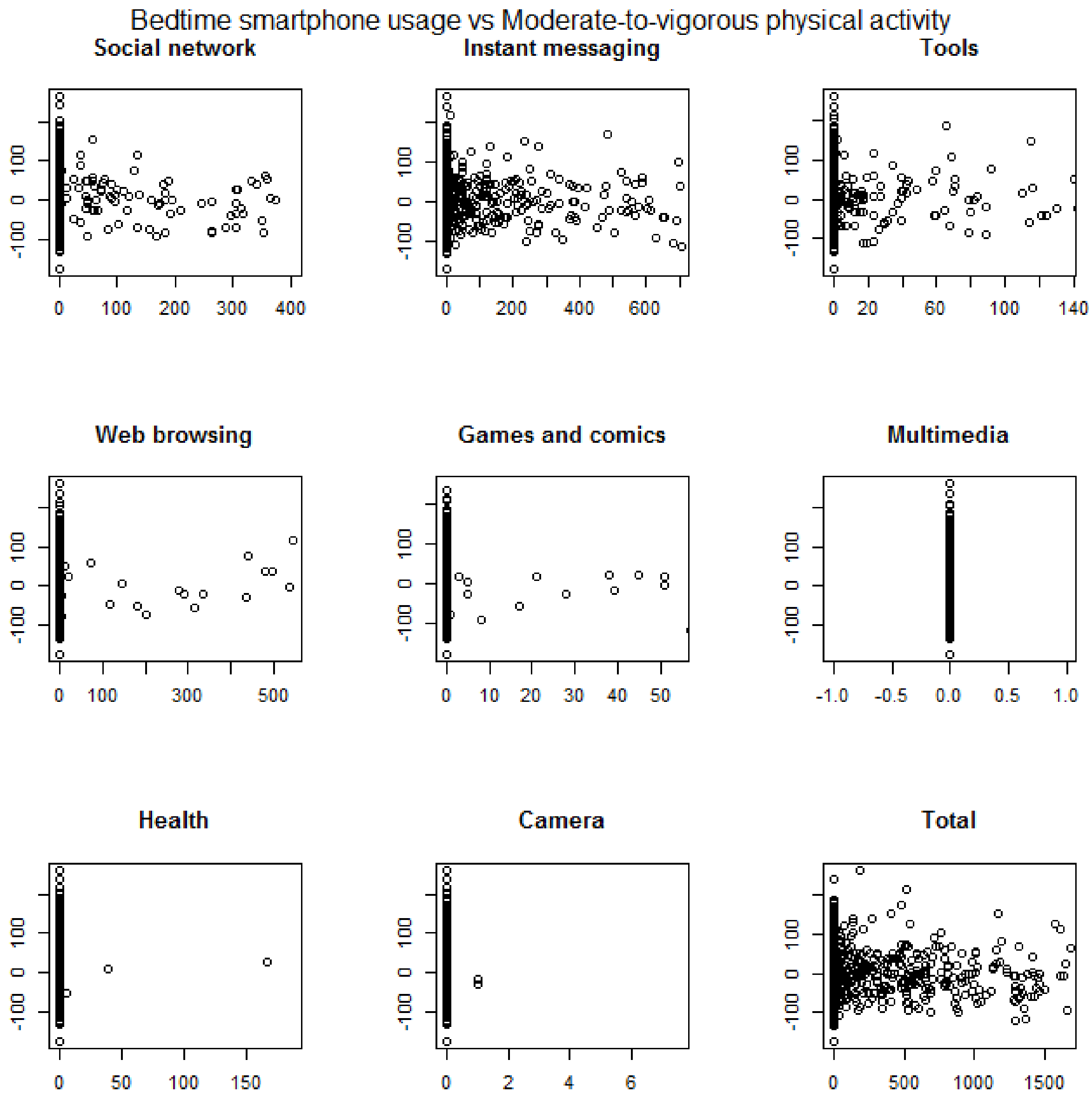

Figure S46. Residual plot of smartphone use during sleep on time spent on moderate-to-vigorous physical activity, university students

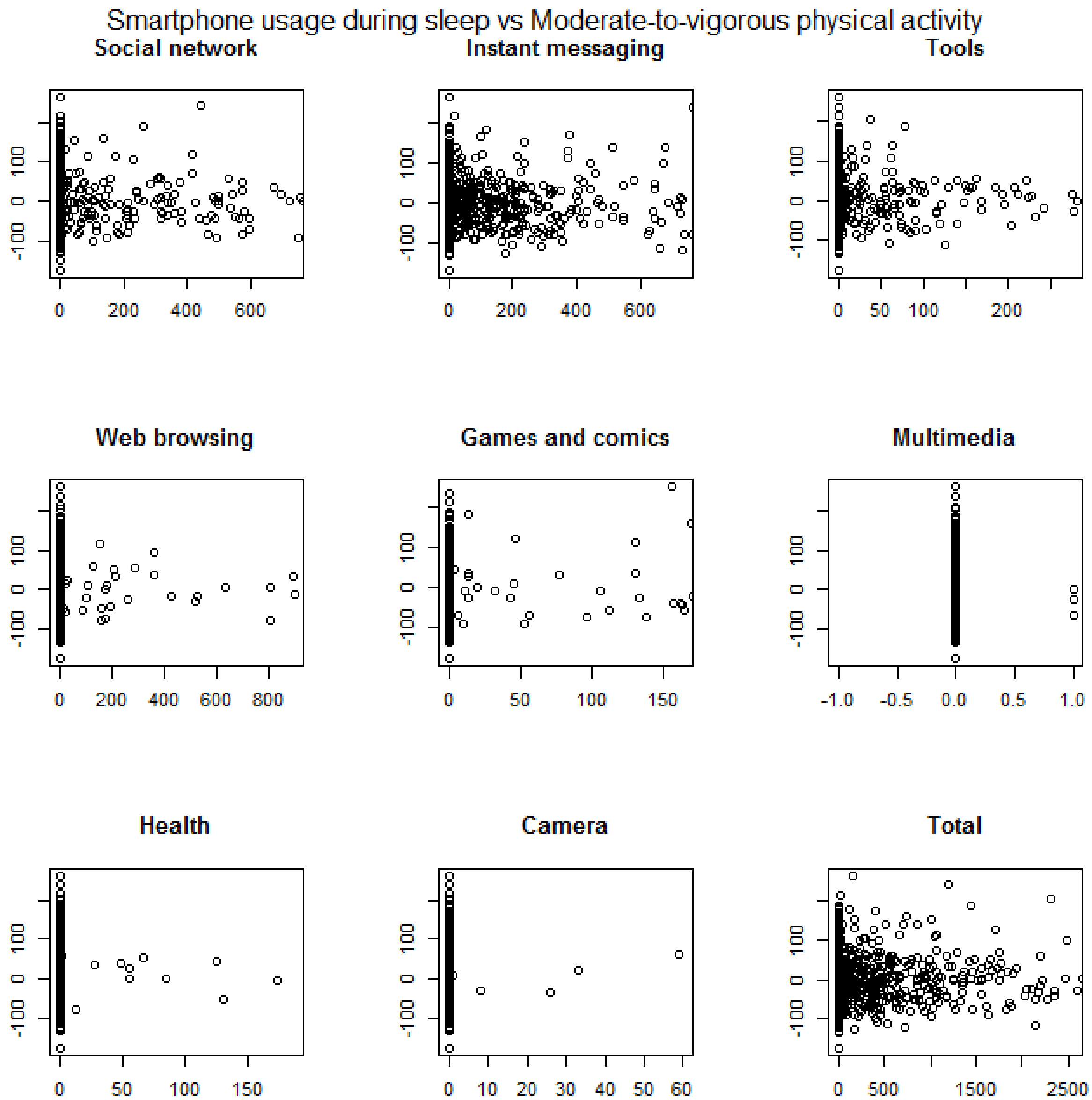

Figure S47. Residual plot of sleep quality on number of steps, university students

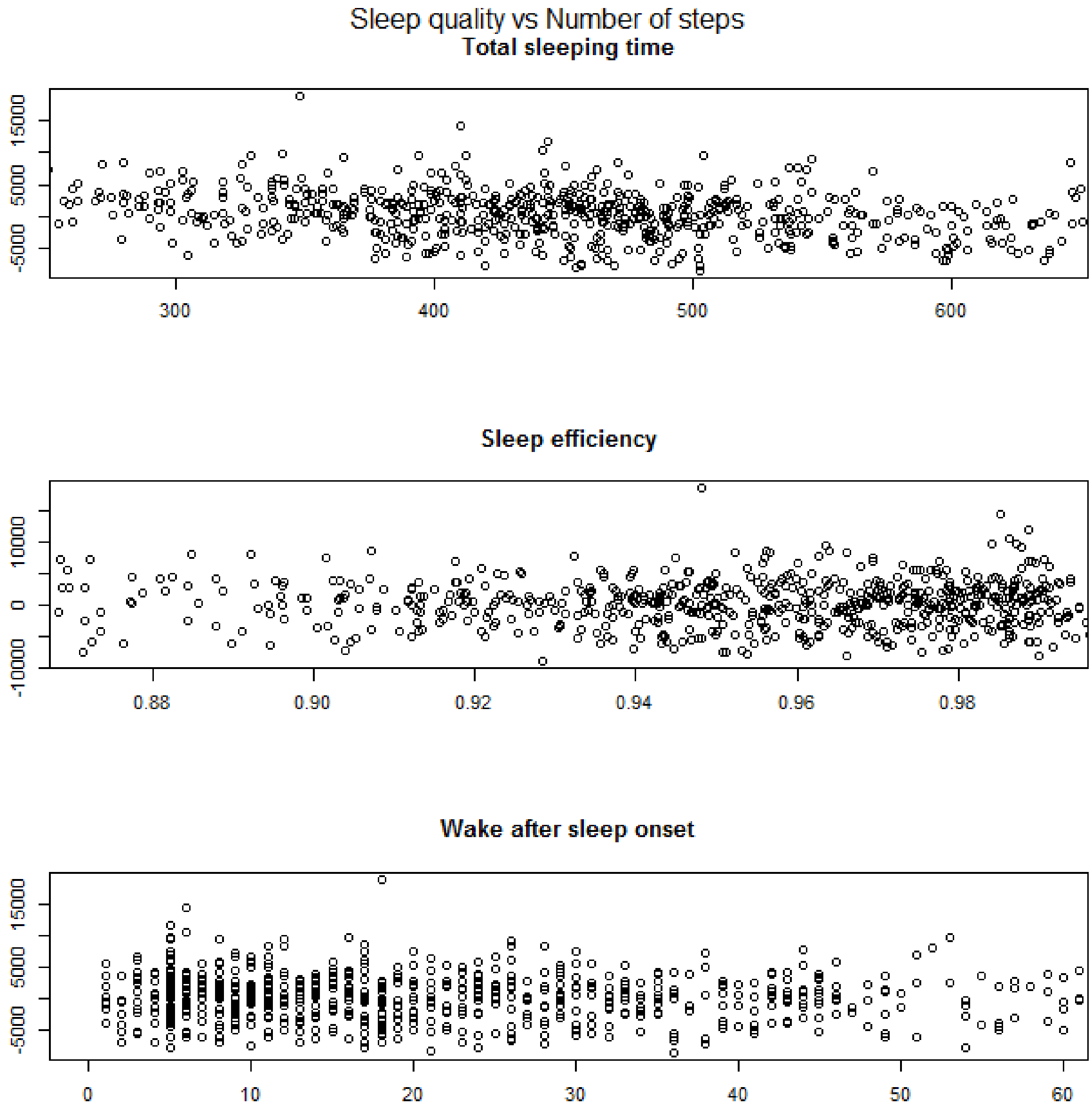

Figure S48. Residual plot of sleep quality on time spent on moderate-to-vigorous physical activity, university students

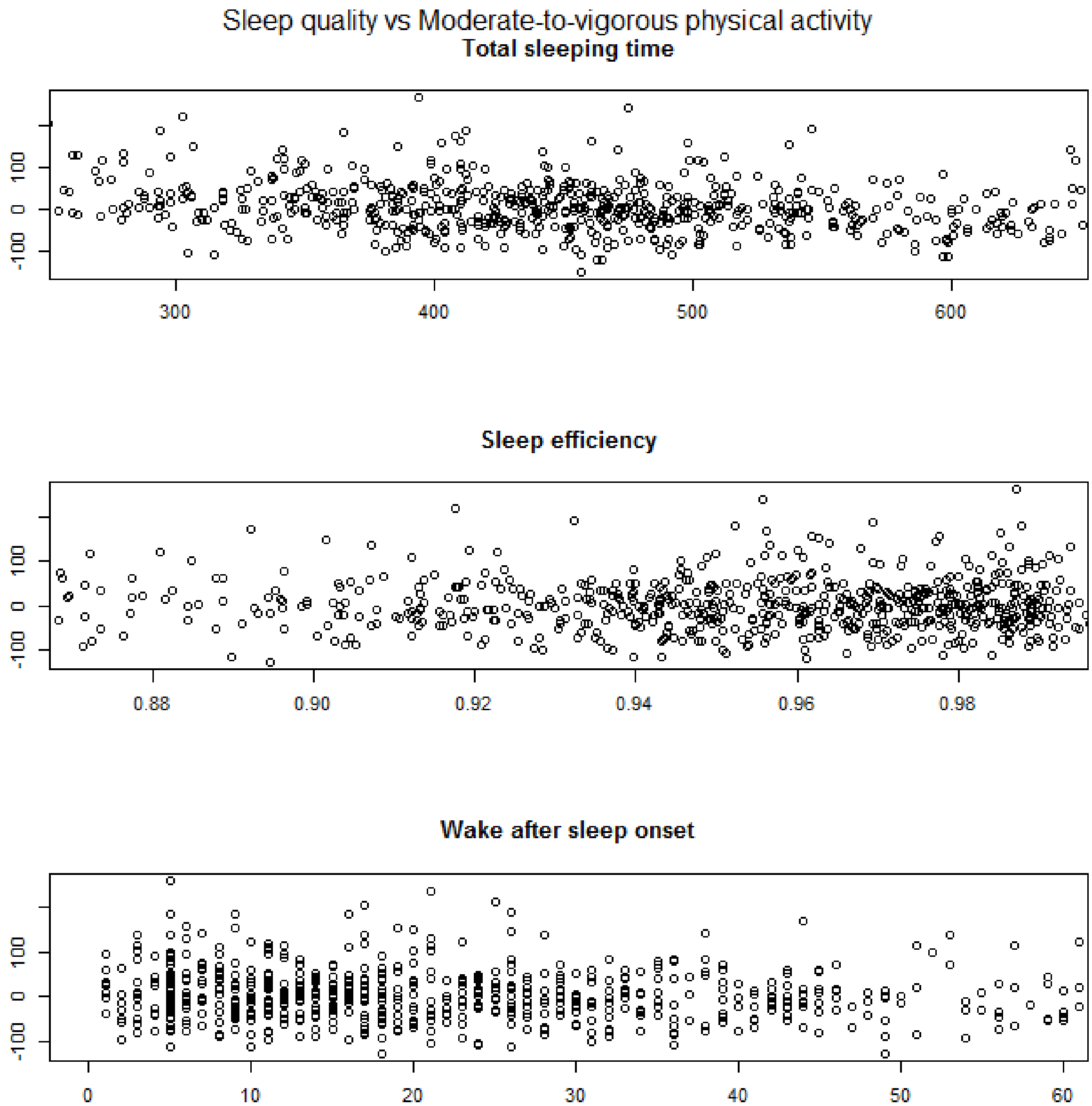

Figure S49. Histogram of the regression residuals of smartphone usage on total sleeping time, overall sample

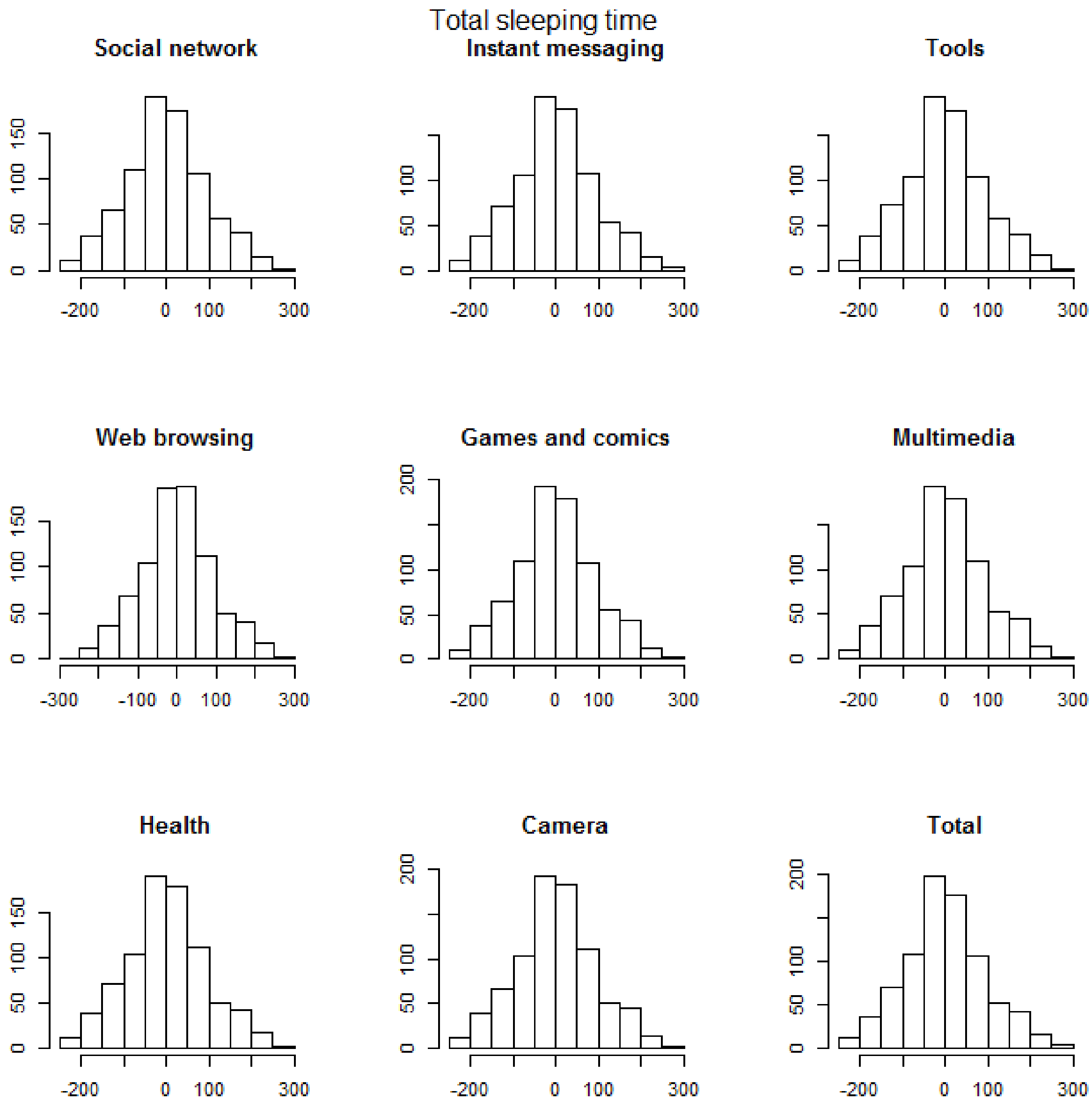

Figure S50. Histogram of the regression residuals of smartphone usage on sleep efficiency, overall sample

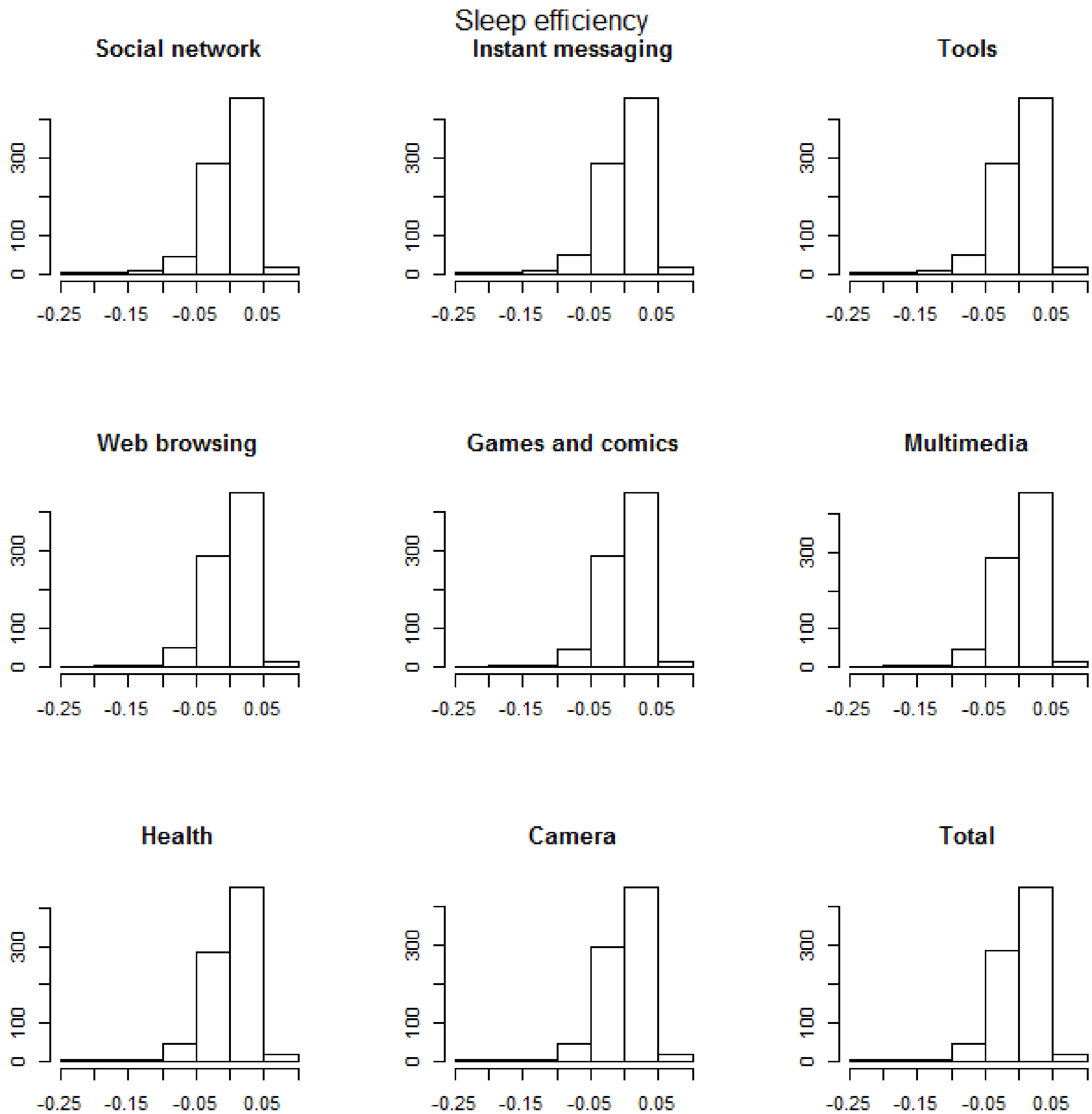

Figure S51. Histogram of the regression residuals of smartphone usage on wake after sleep onset, overall sample

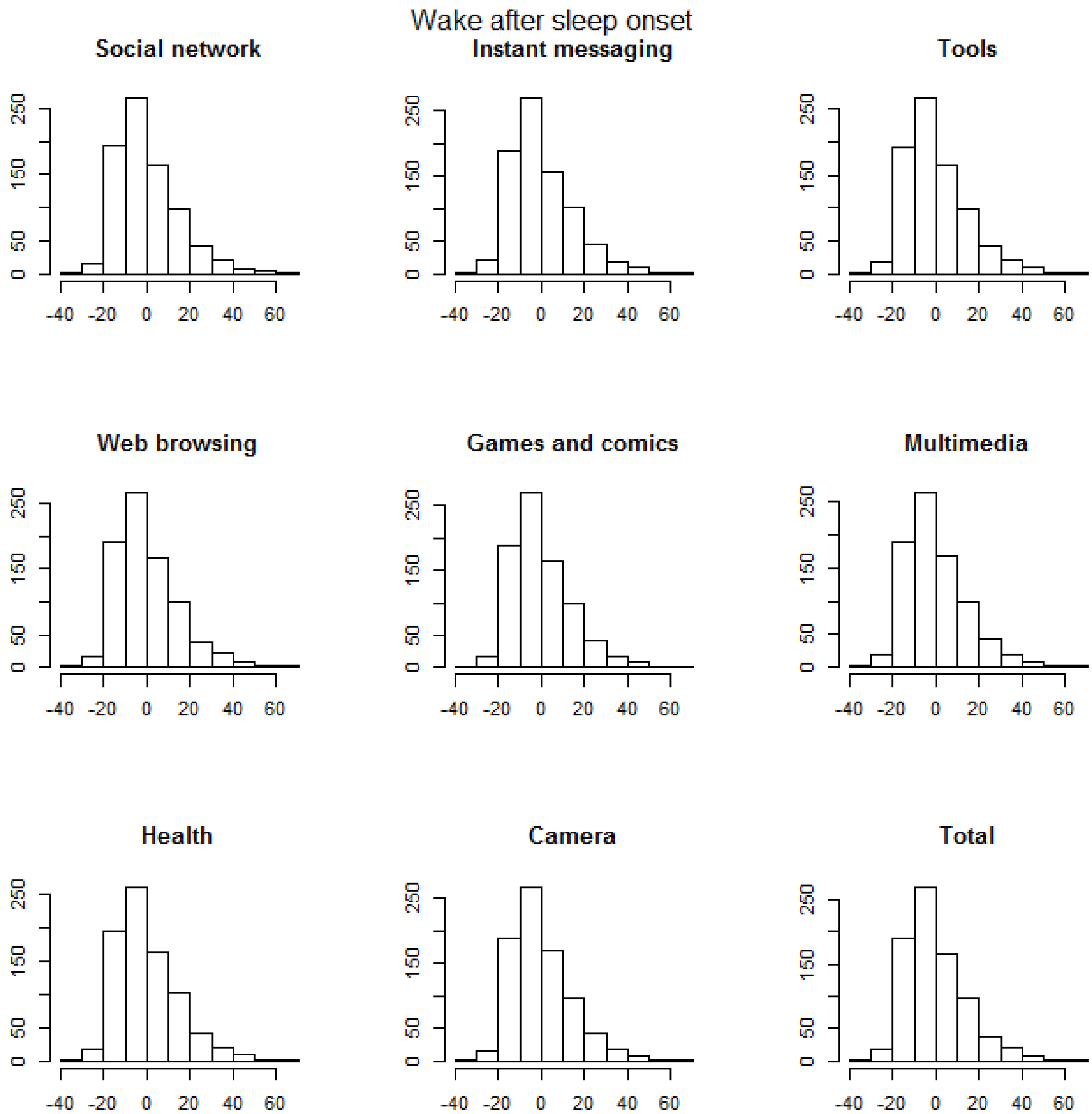

Figure S52. Histogram of the regression residuals of smartphone usage on number of steps, overall sample

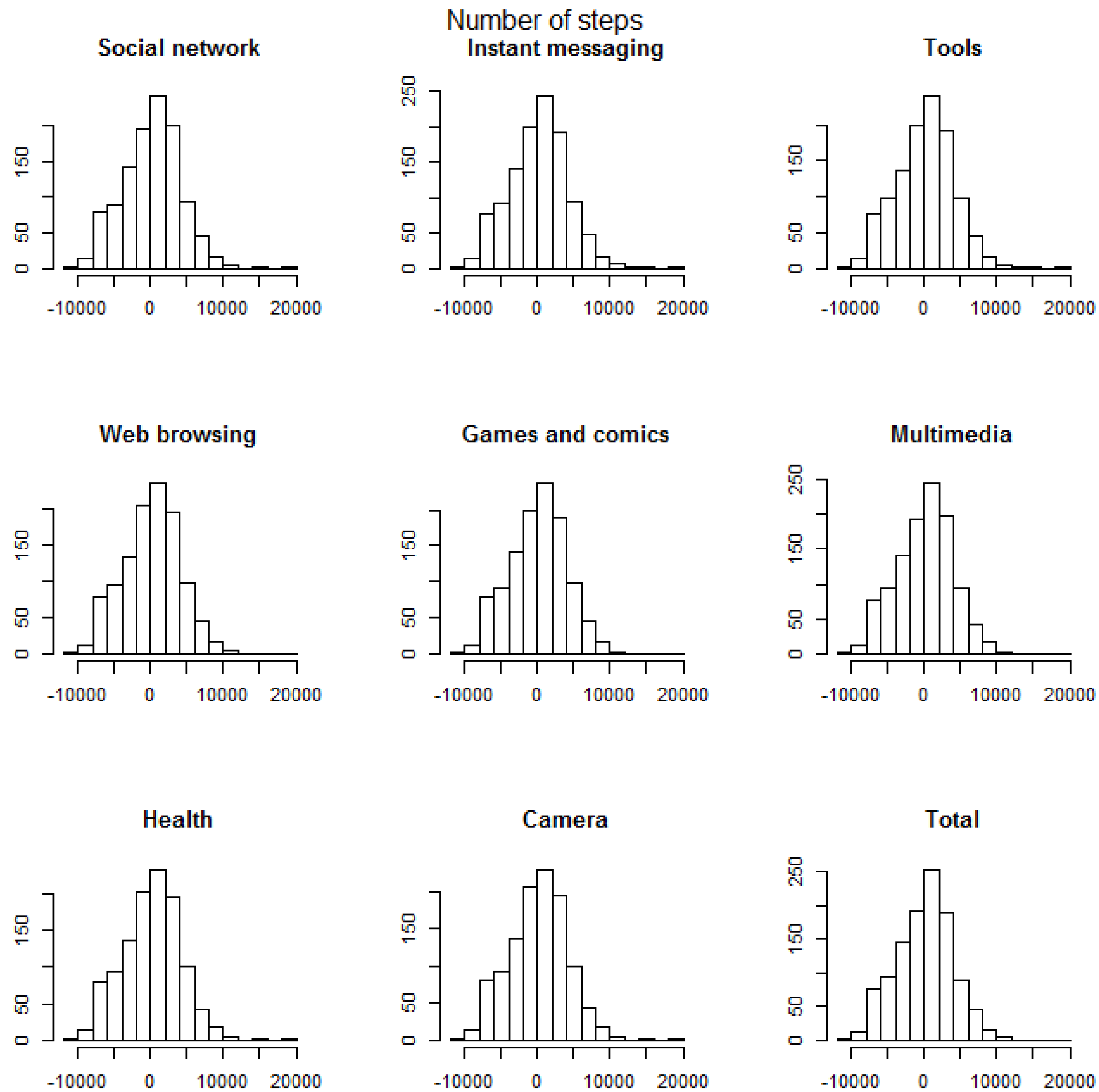

Figure S53. Histogram of the regression residuals of smartphone usage on moderate-to-vigorous physical activity, overall sample

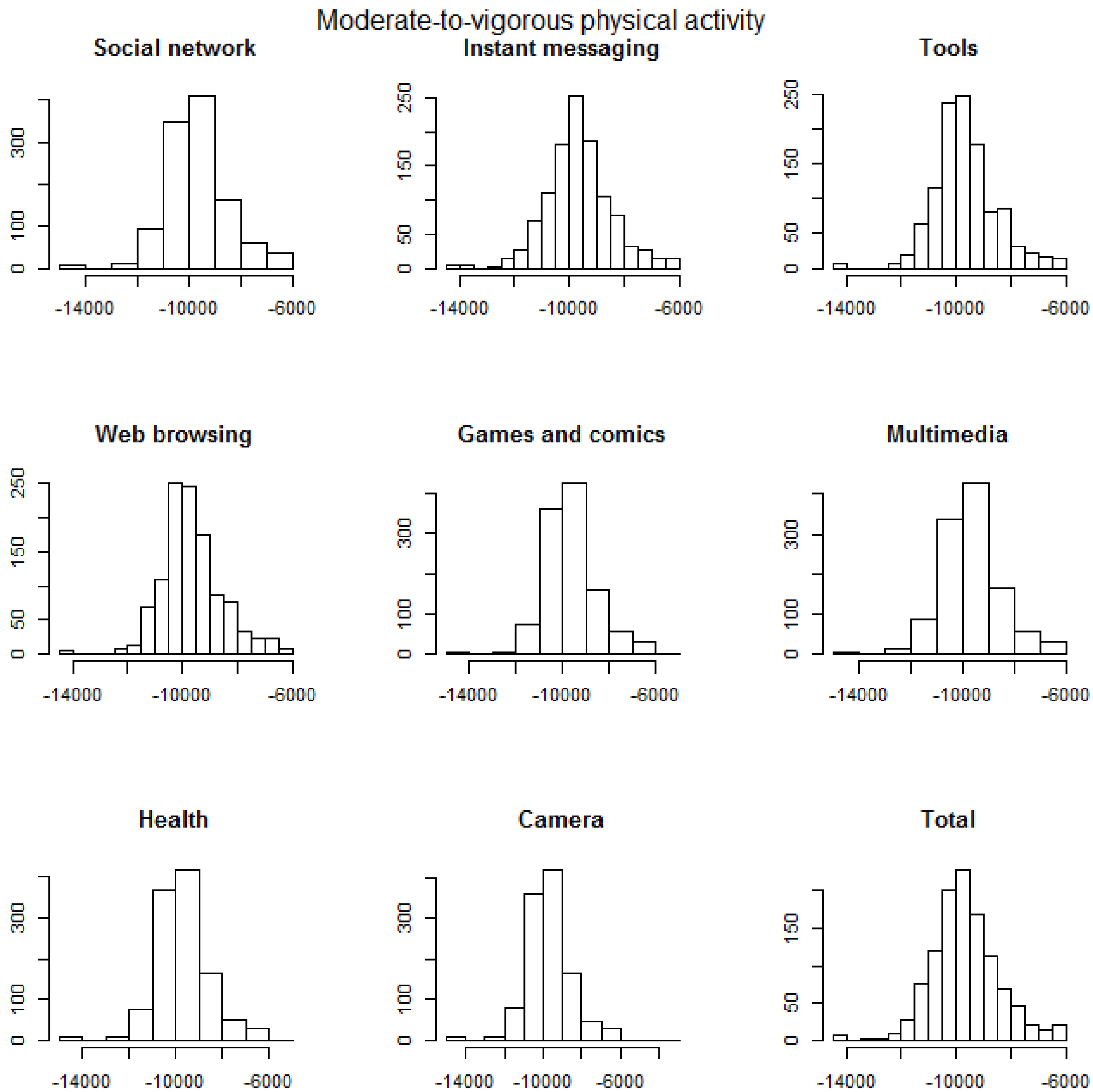

Figure S54. Histogram of the regression residuals of sleep quality on number of steps, overall sample

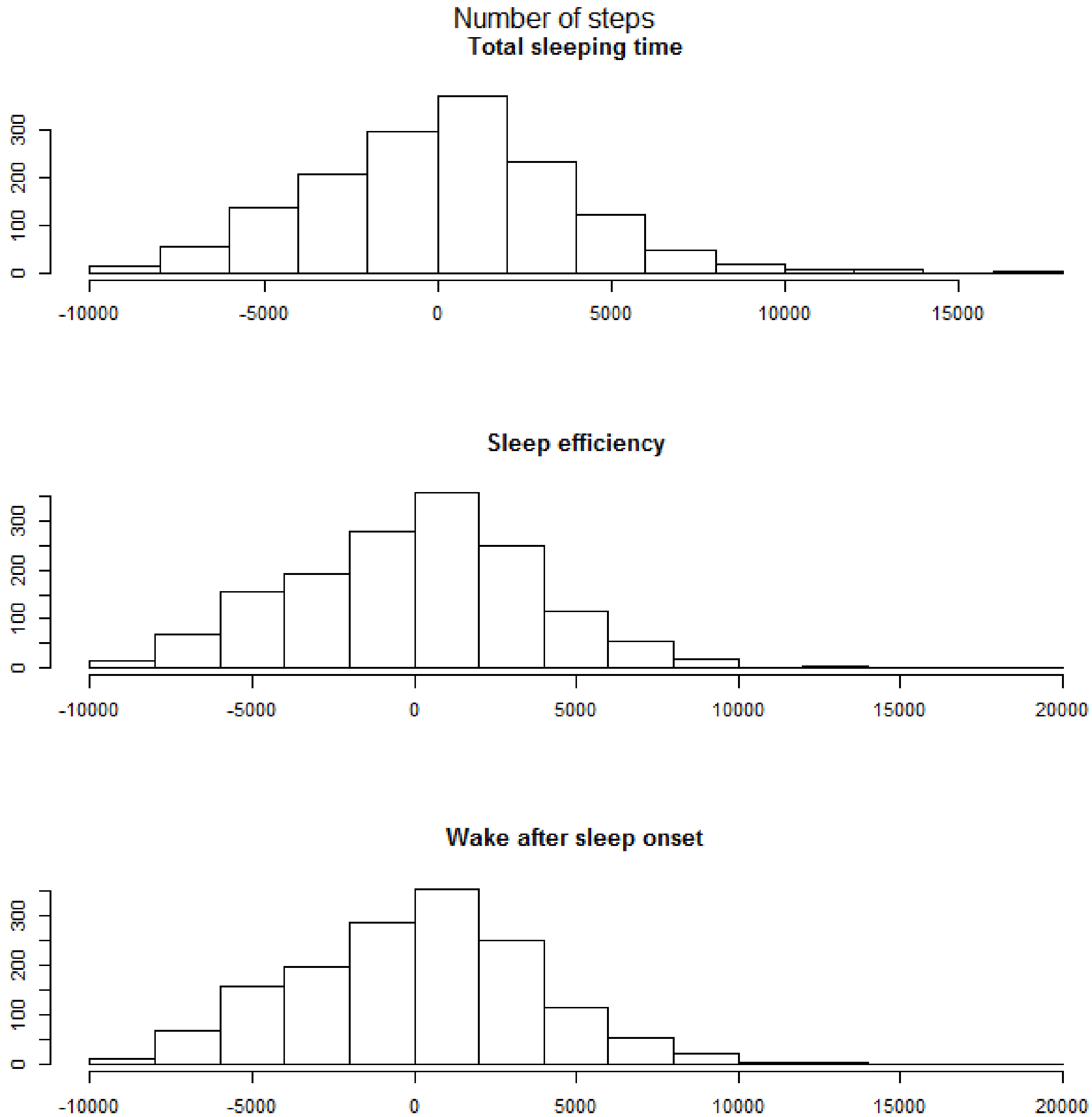

Figure S55. Histogram of the regression residuals of sleep quality on moderate-to-vigorous physical activity, overall sample

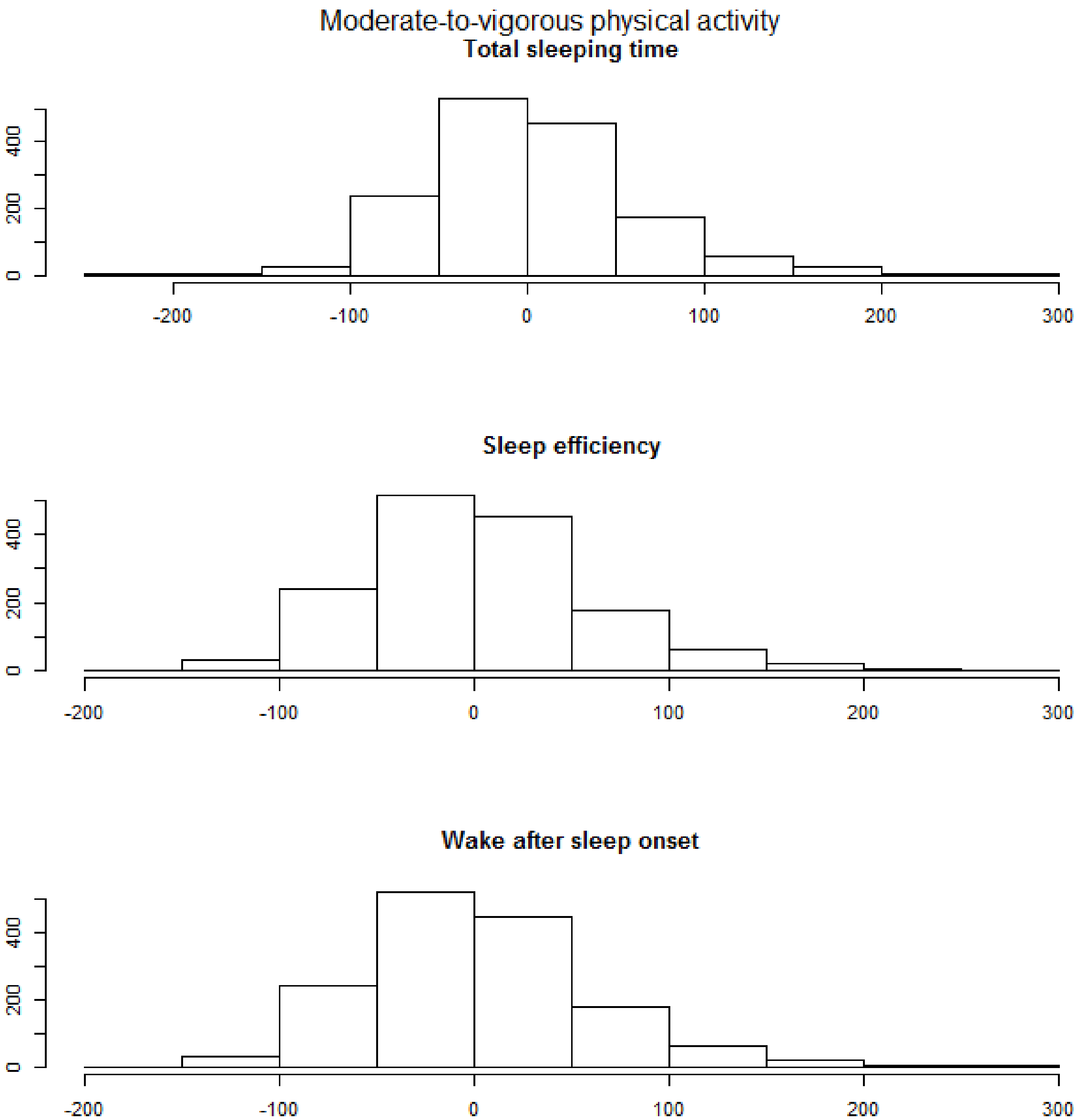

Figure S56. Residual plot of daytime smartphone use on total sleeping time, overall sample

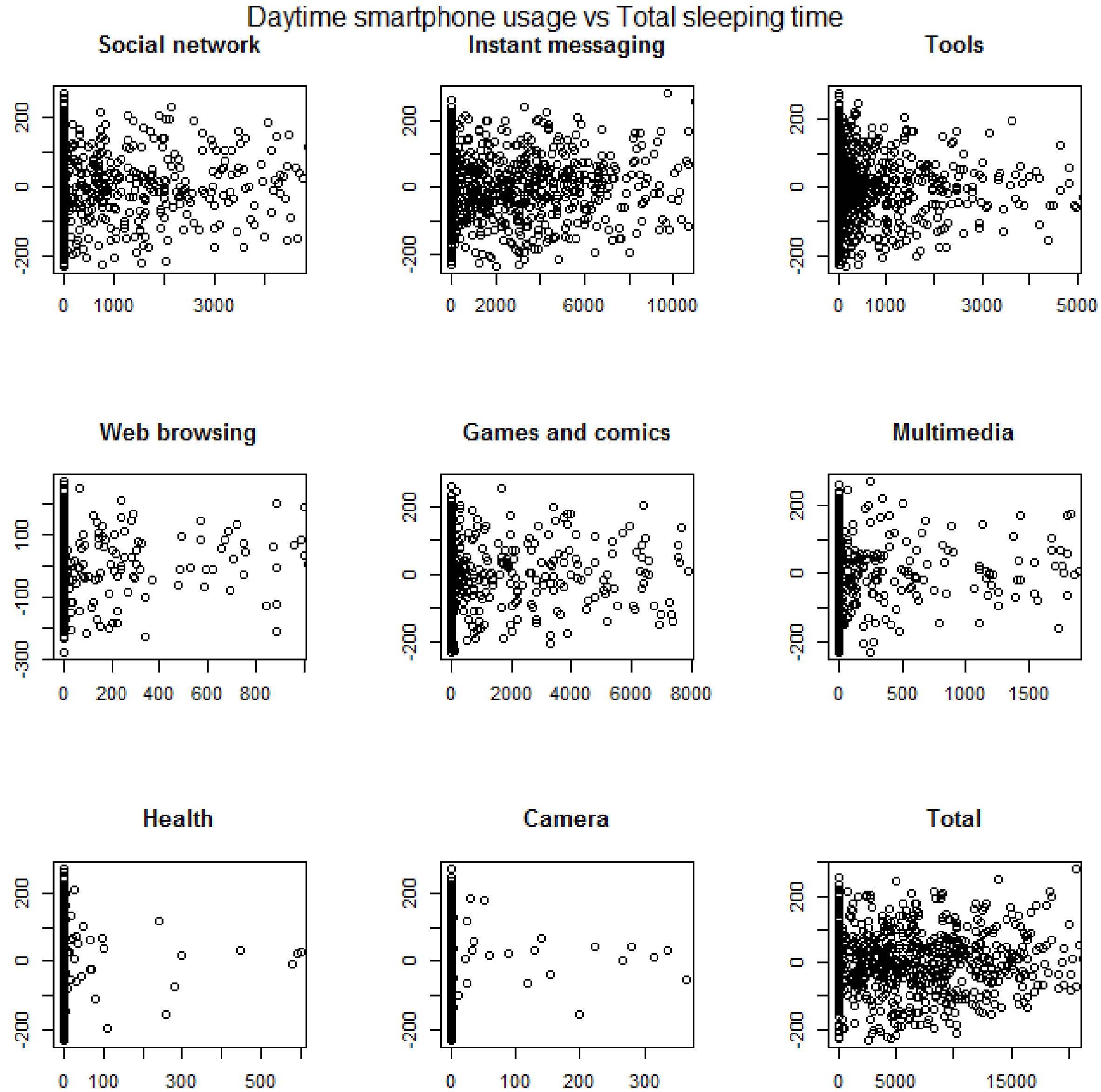

Figure S57. Residual plot of bedtime smartphone use on total sleeping time, overall sample

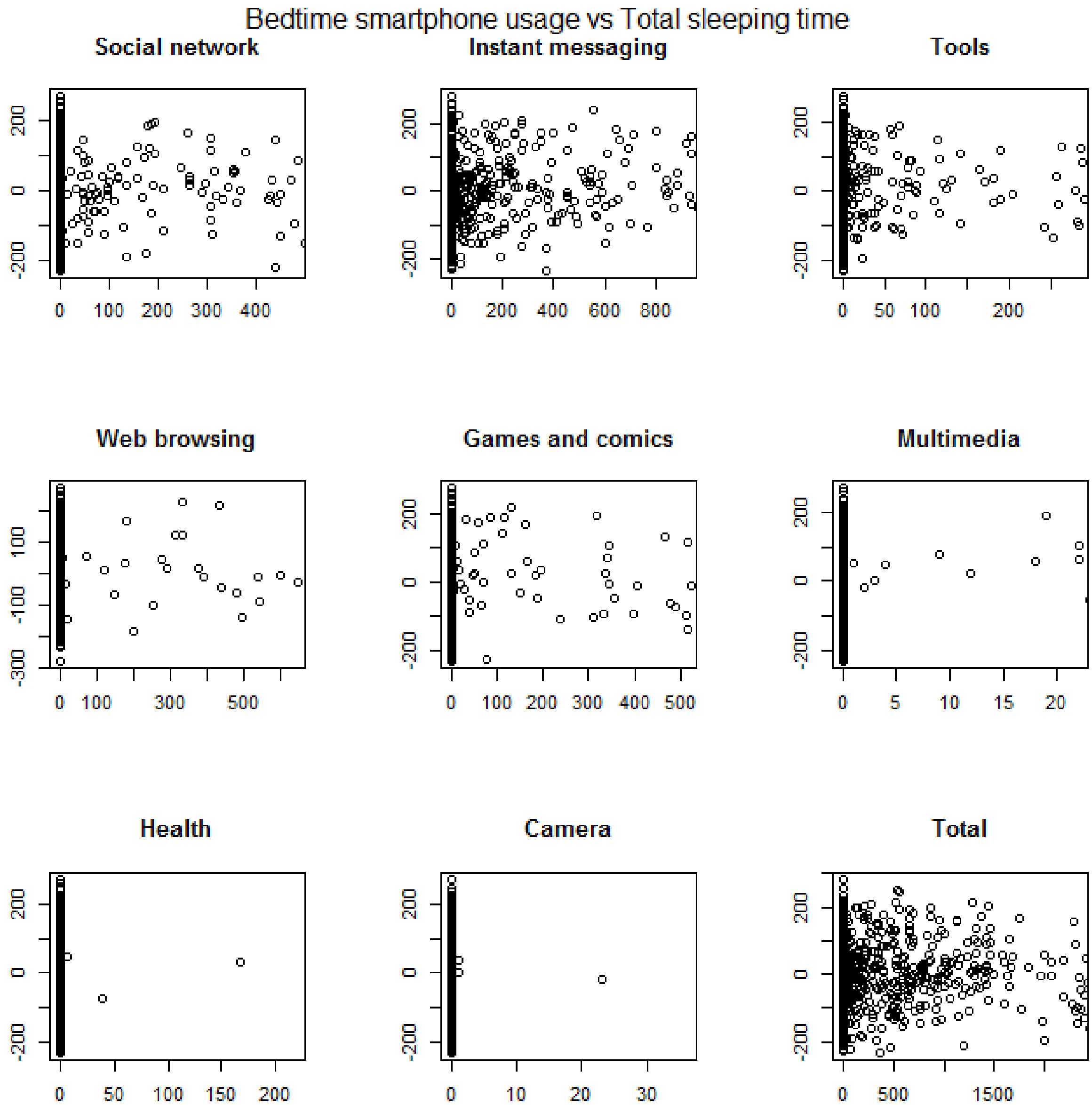

Figure S58. Residual plot of smartphone use during sleep on total sleeping time, overall sample

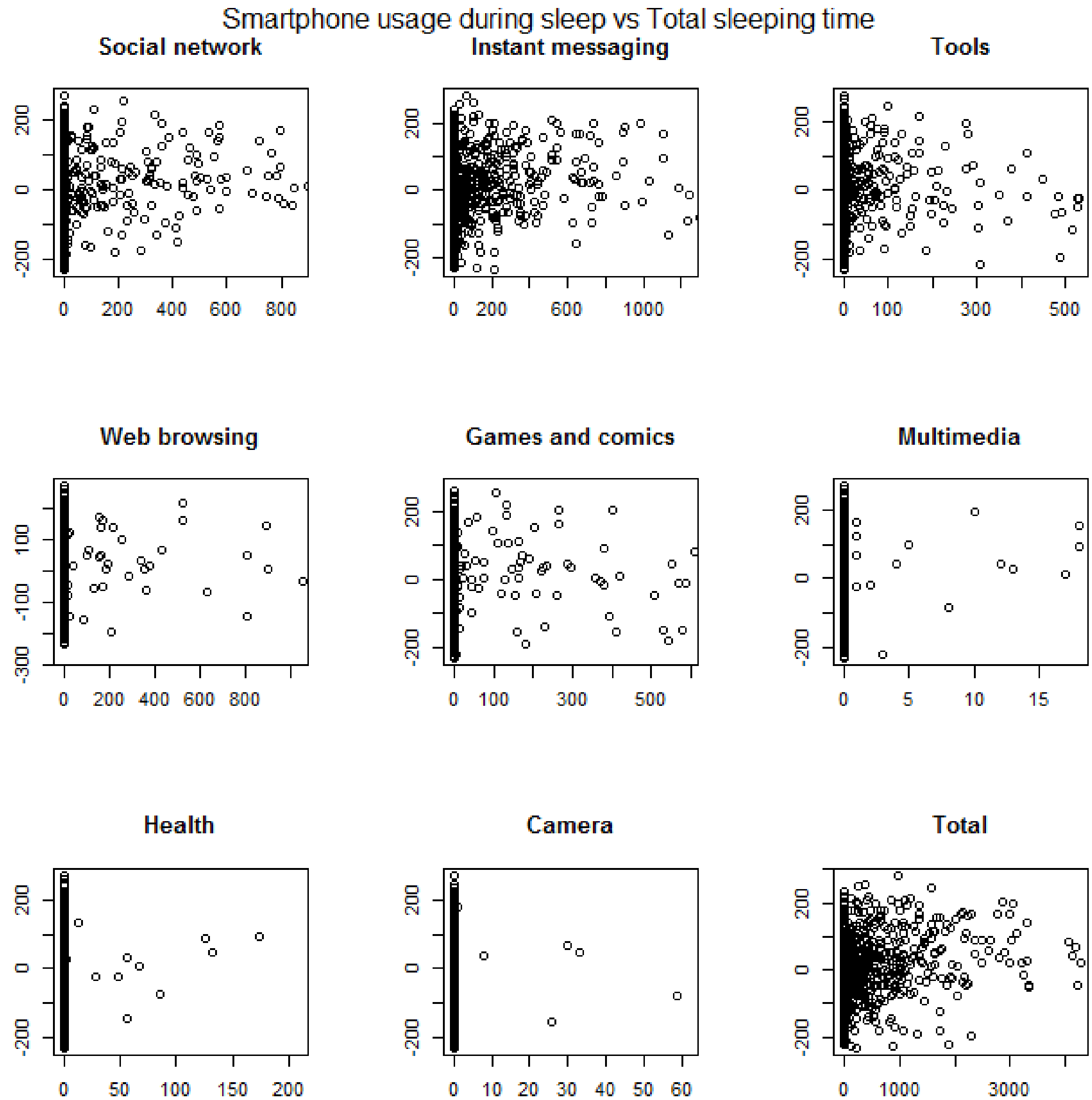

Figure S59. Residual plot of daytime smartphone use on sleep efficiency, overall sample

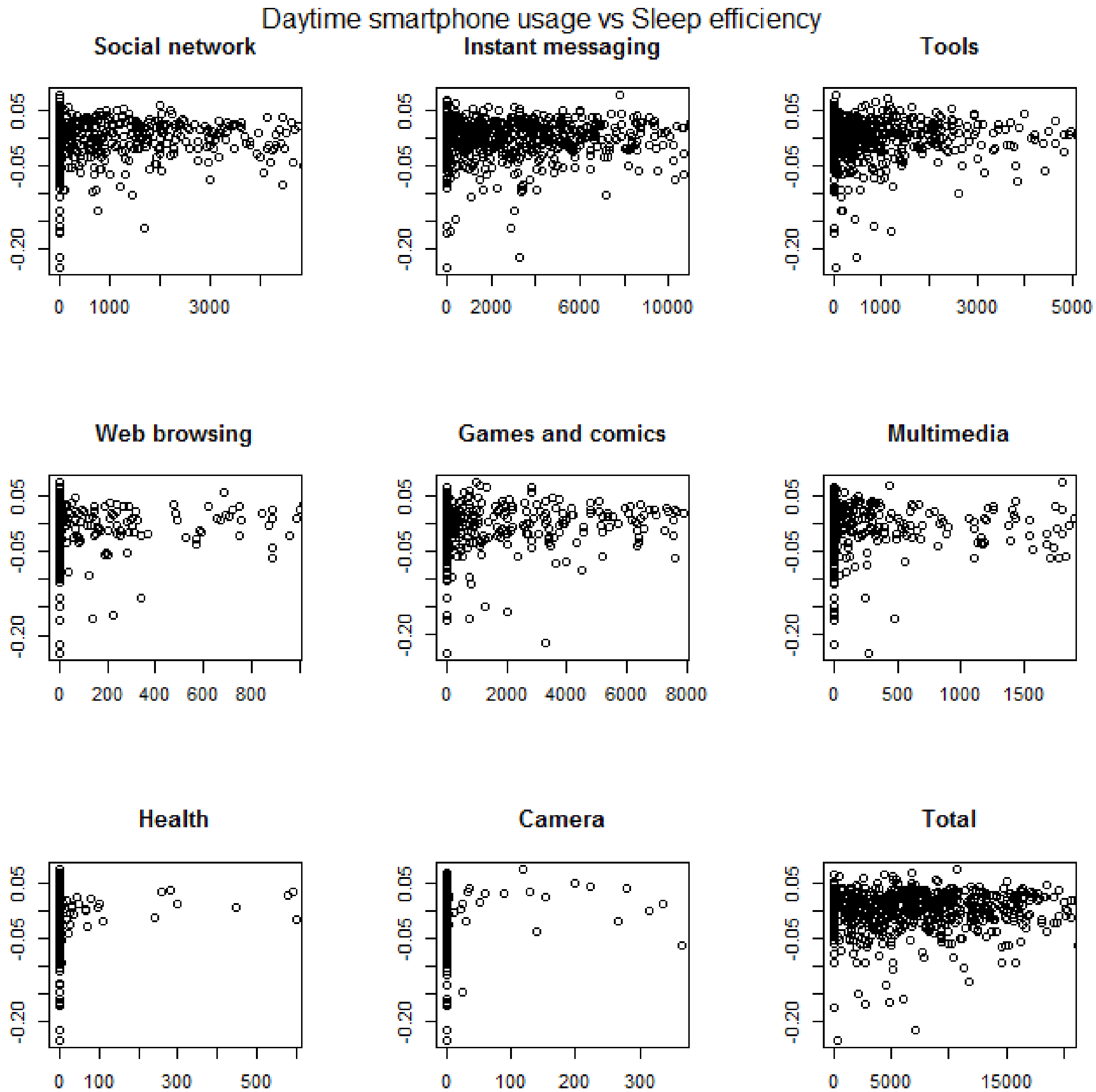

Figure S60. Residual plot of bedtime smartphone use on sleep efficiency, overall sample

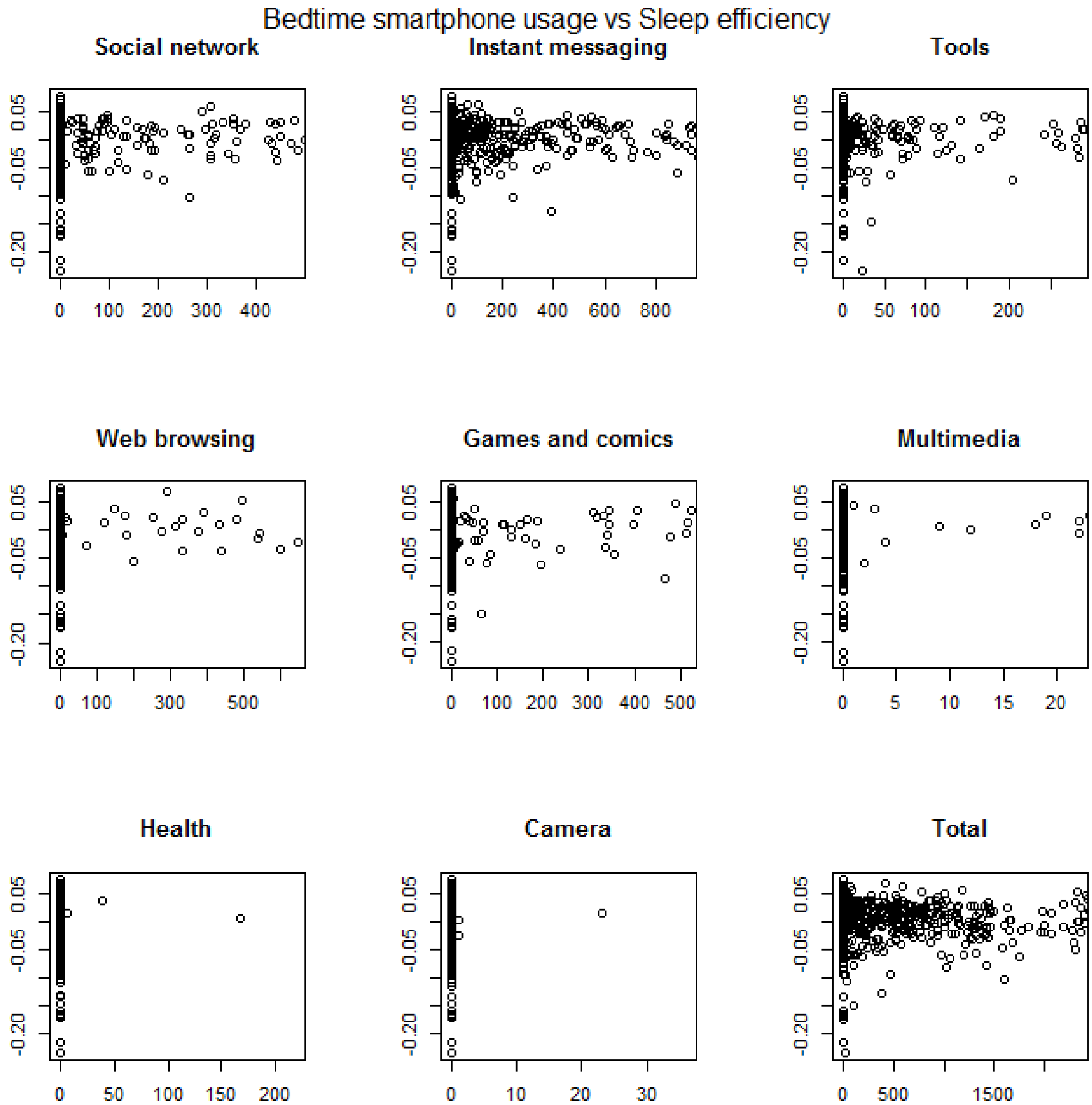

Figure S61. Residual plot of smartphone use during sleep on sleep efficiency, overall sample

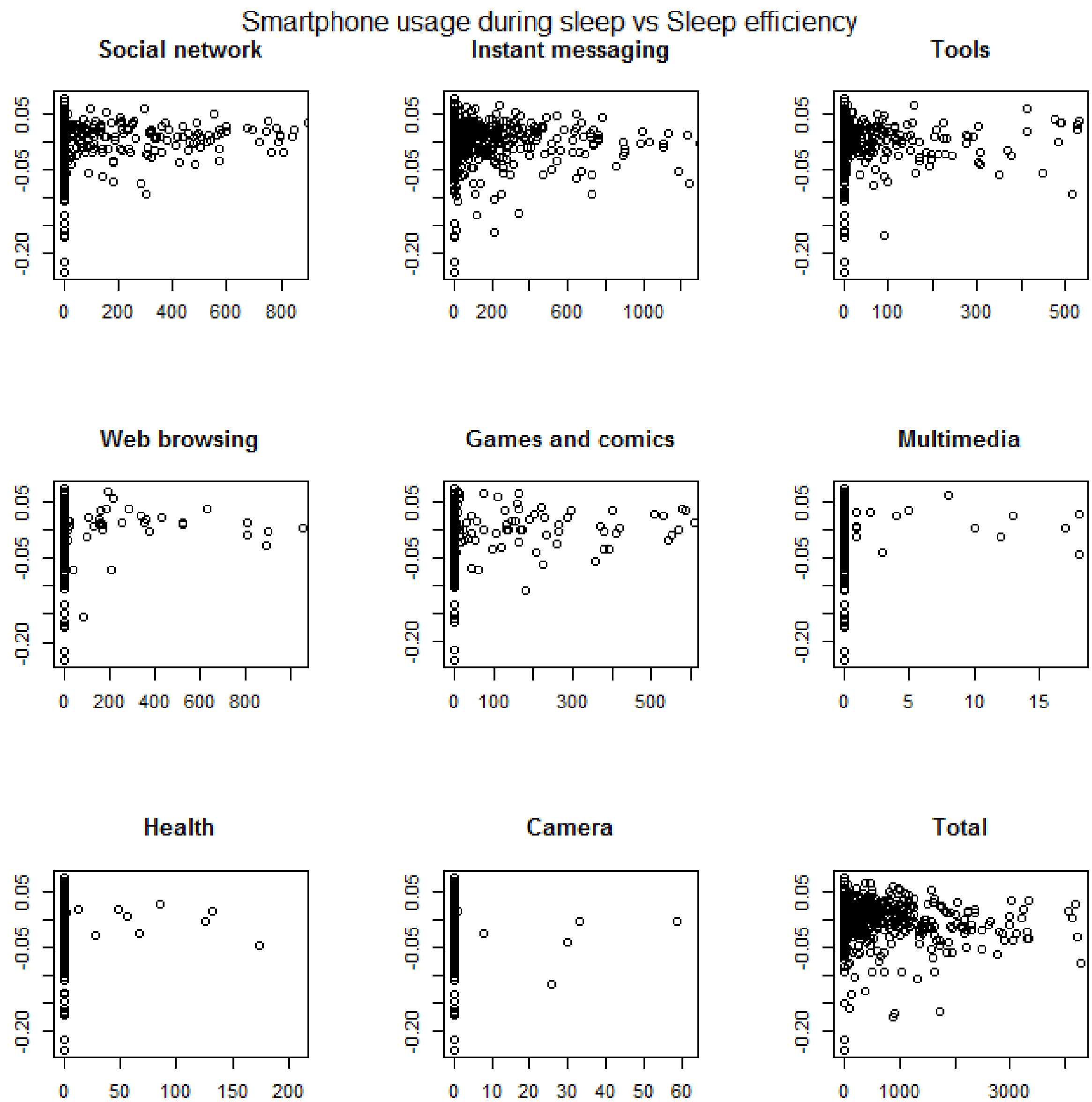

Figure S62. Residual plot of daytime smartphone use on wake after sleep onset, overall sample

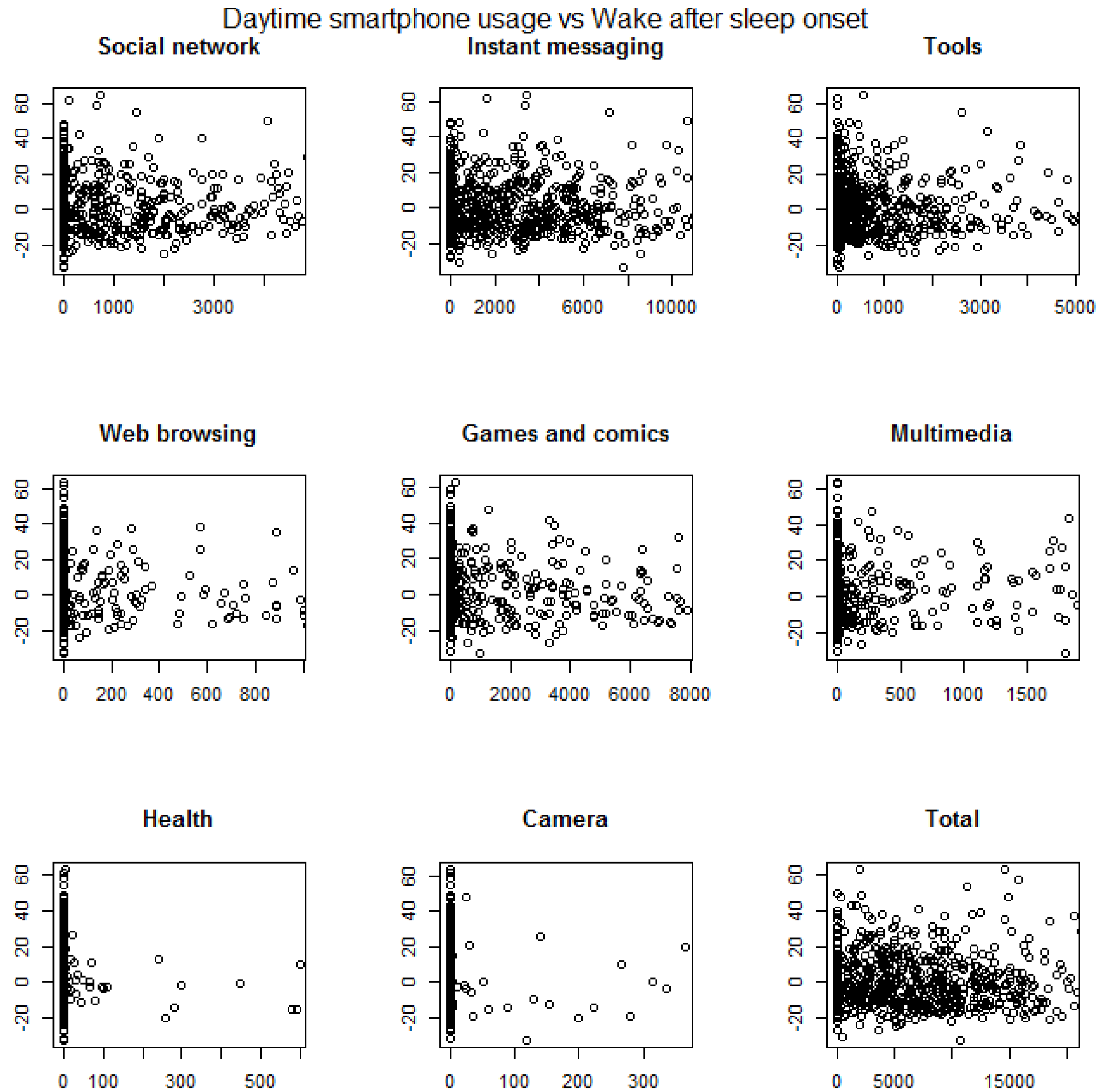

Figure S63. Residual plot of bedtime smartphone use on wake after sleep onset, overall sample

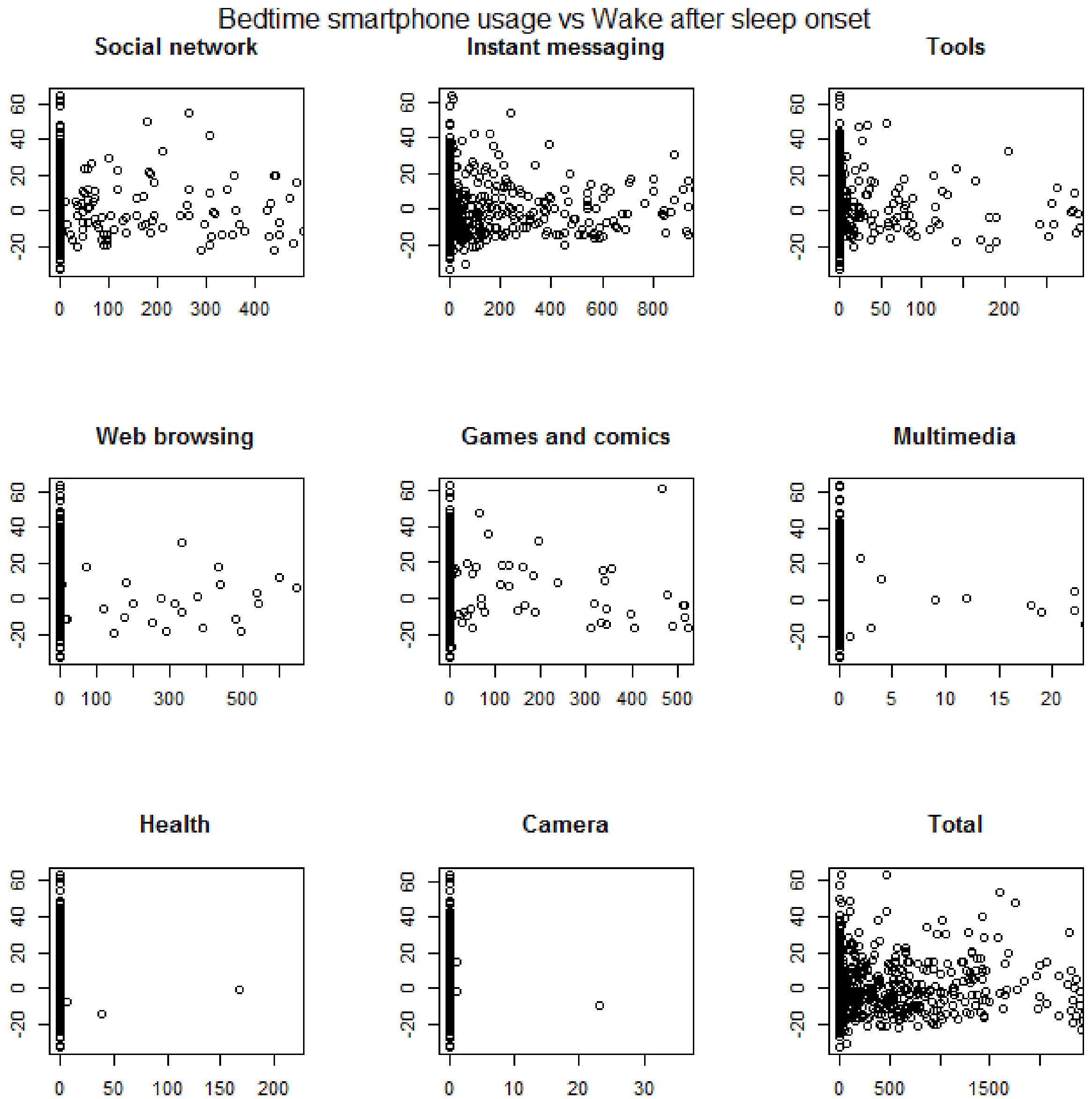

Figure S64. Residual plot of smartphone use during sleep on wake after sleep onset, overall sample

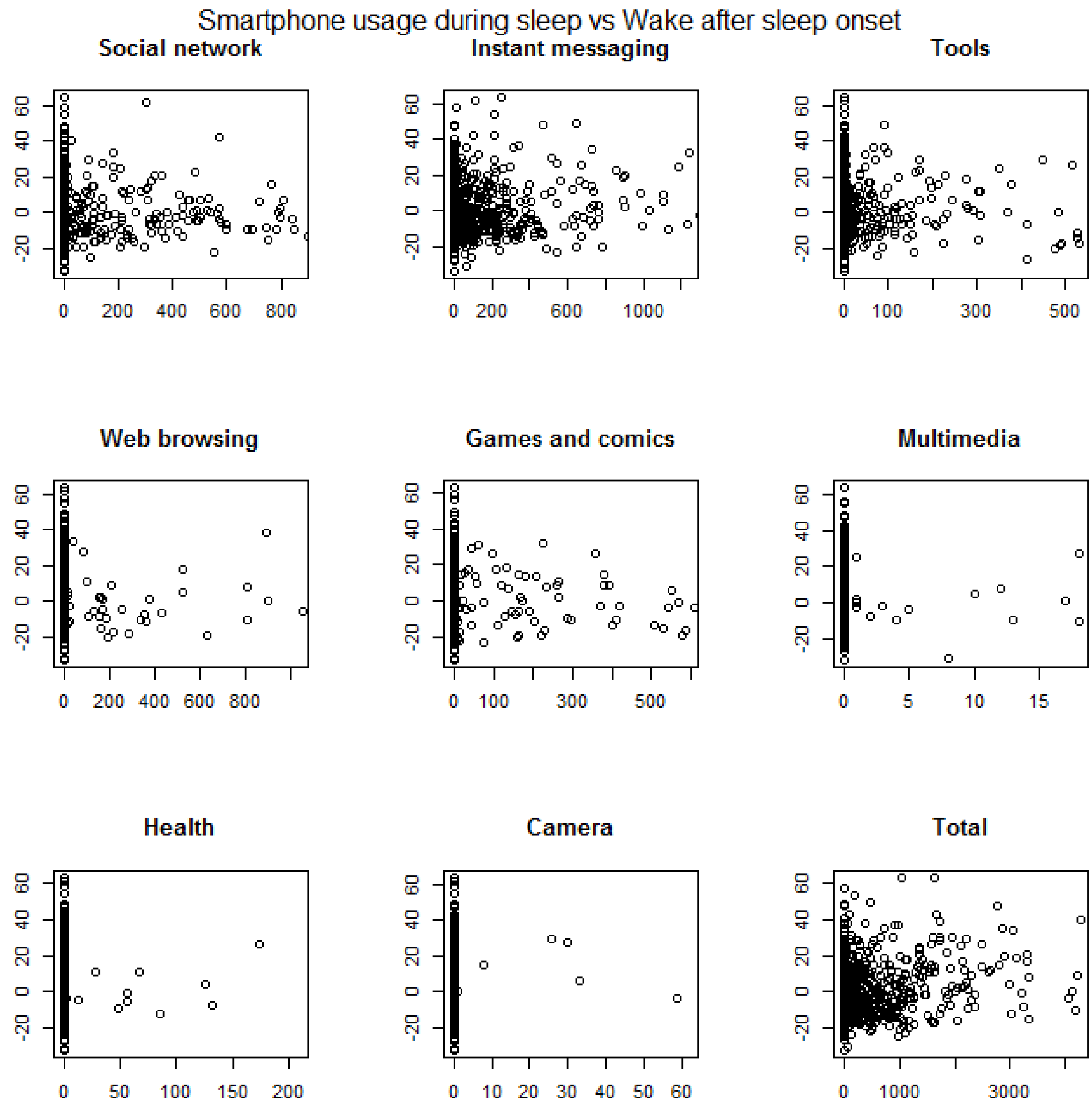

Figure S65. Residual plot of daytime smartphone on number of steps, overall sample

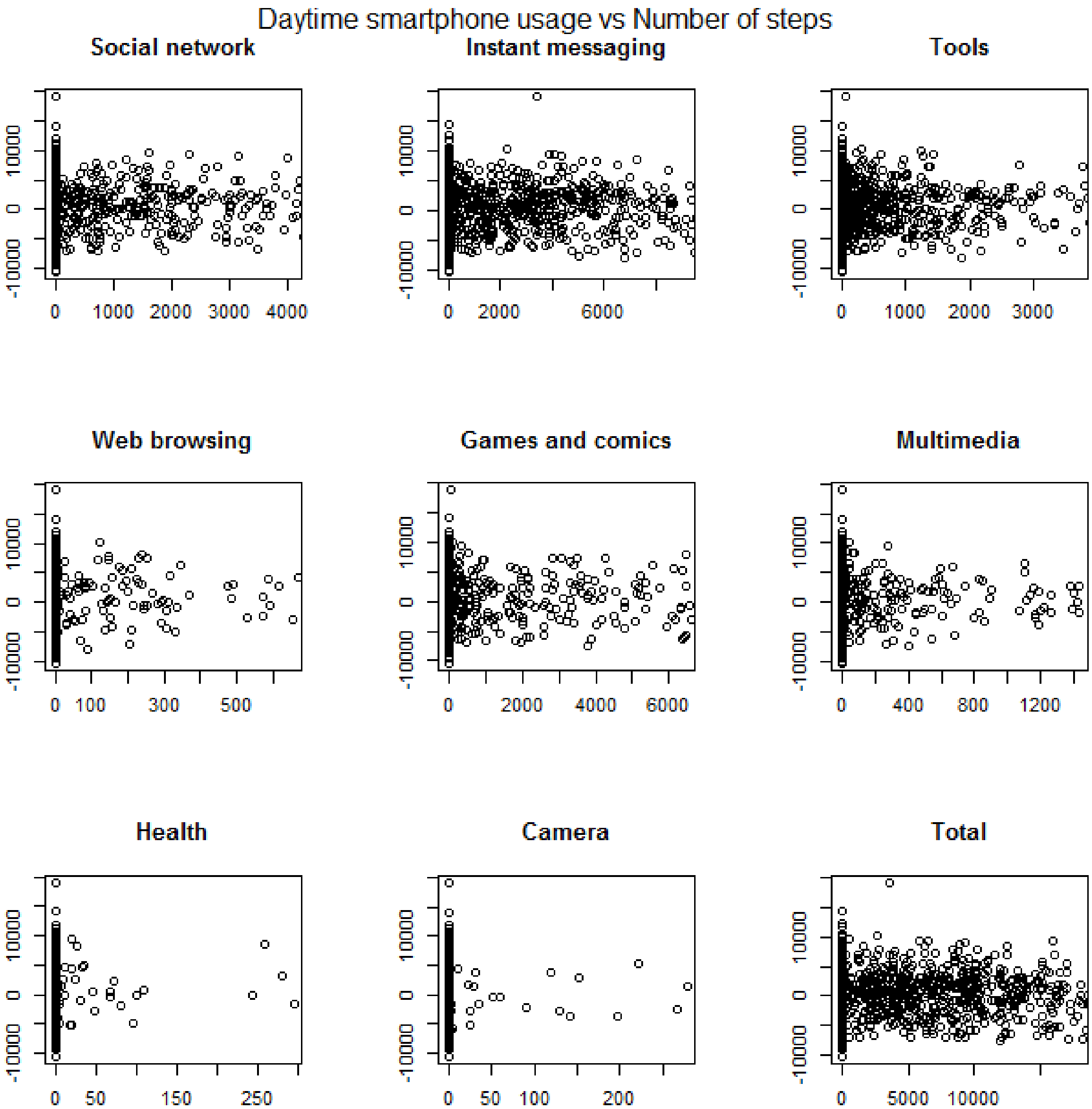

Figure S66. Residual plot of bedtime smartphone on number of steps, overall sample

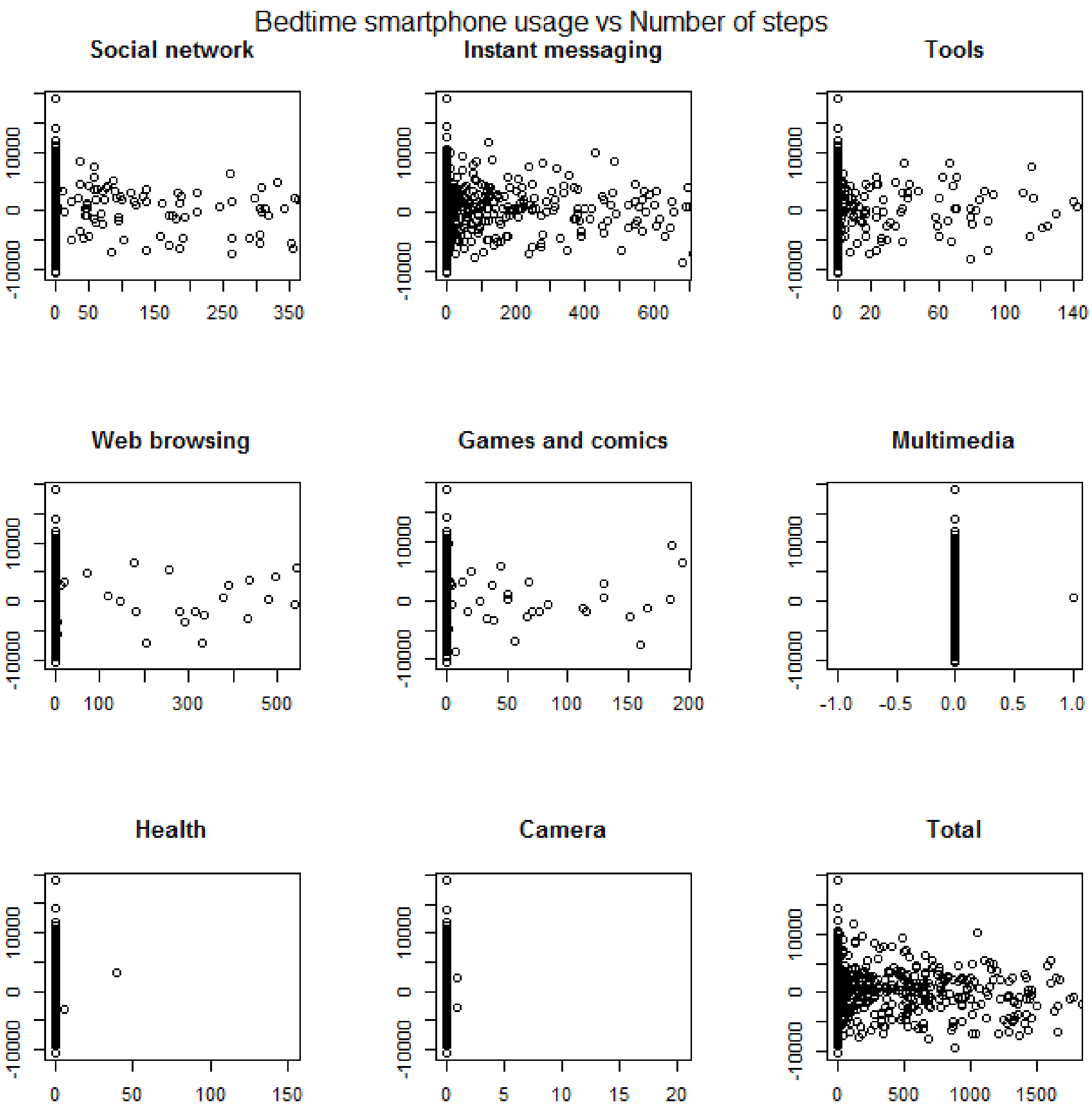

Figure S67. Residual plot of smartphone use during sleep on number of steps, overall sample

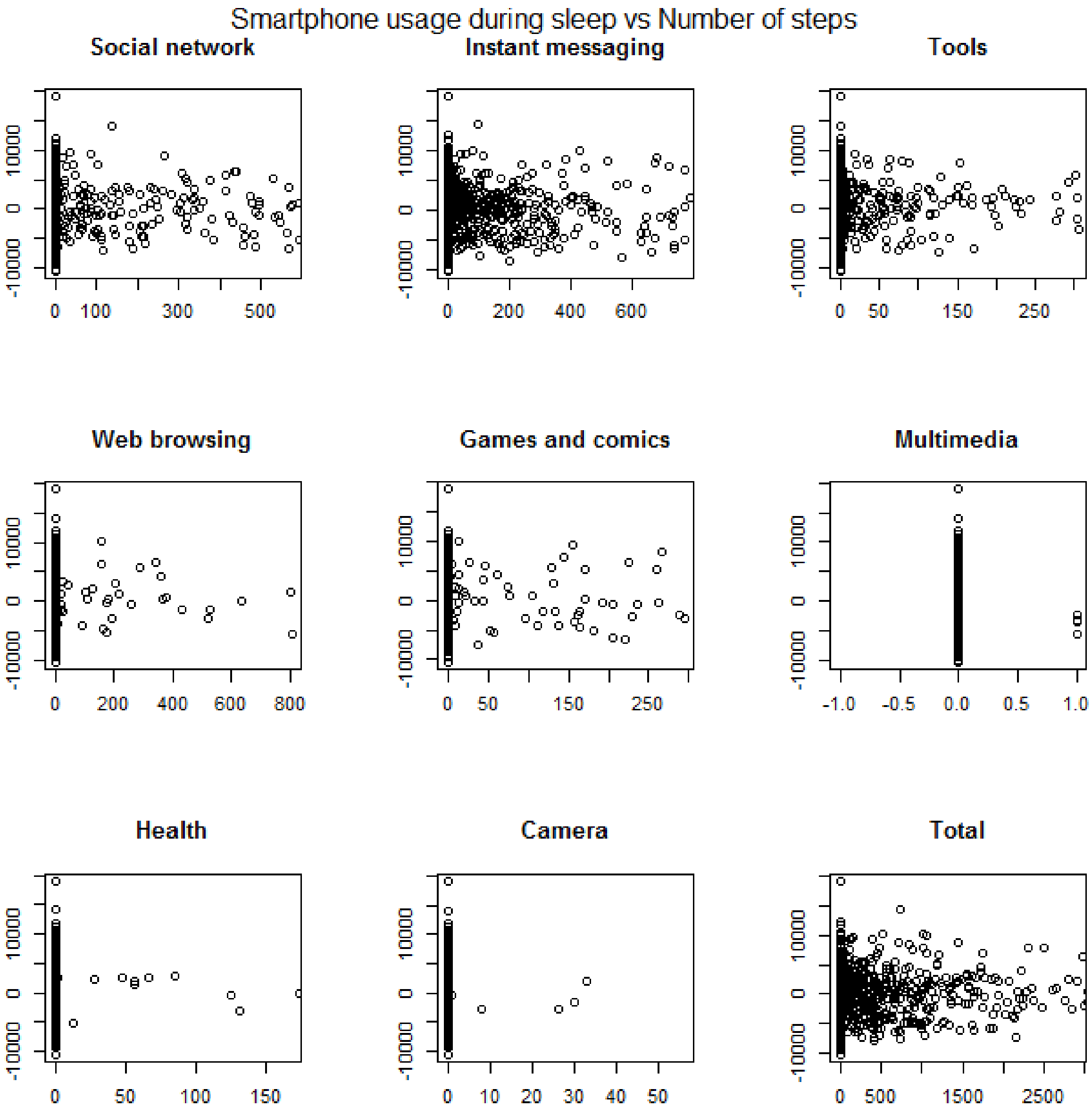

Figure S68. Residual plot of daytime smartphone on time spent on moderate-to-vigorous physical activity, overall sample

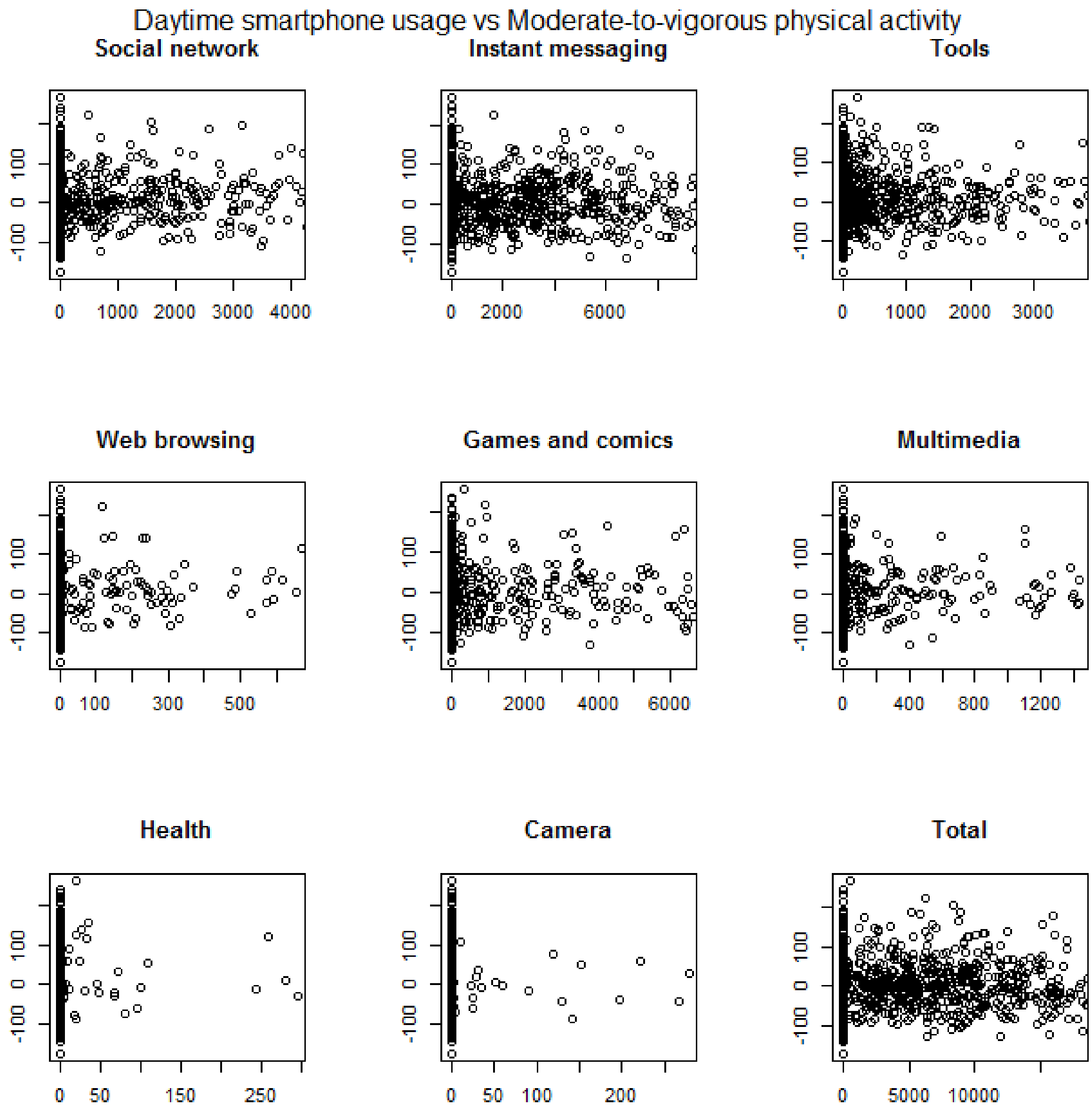

Figure S69. Residual plot of bedtime smartphone on time spent on moderate-to-vigorous physical activity, overall sample

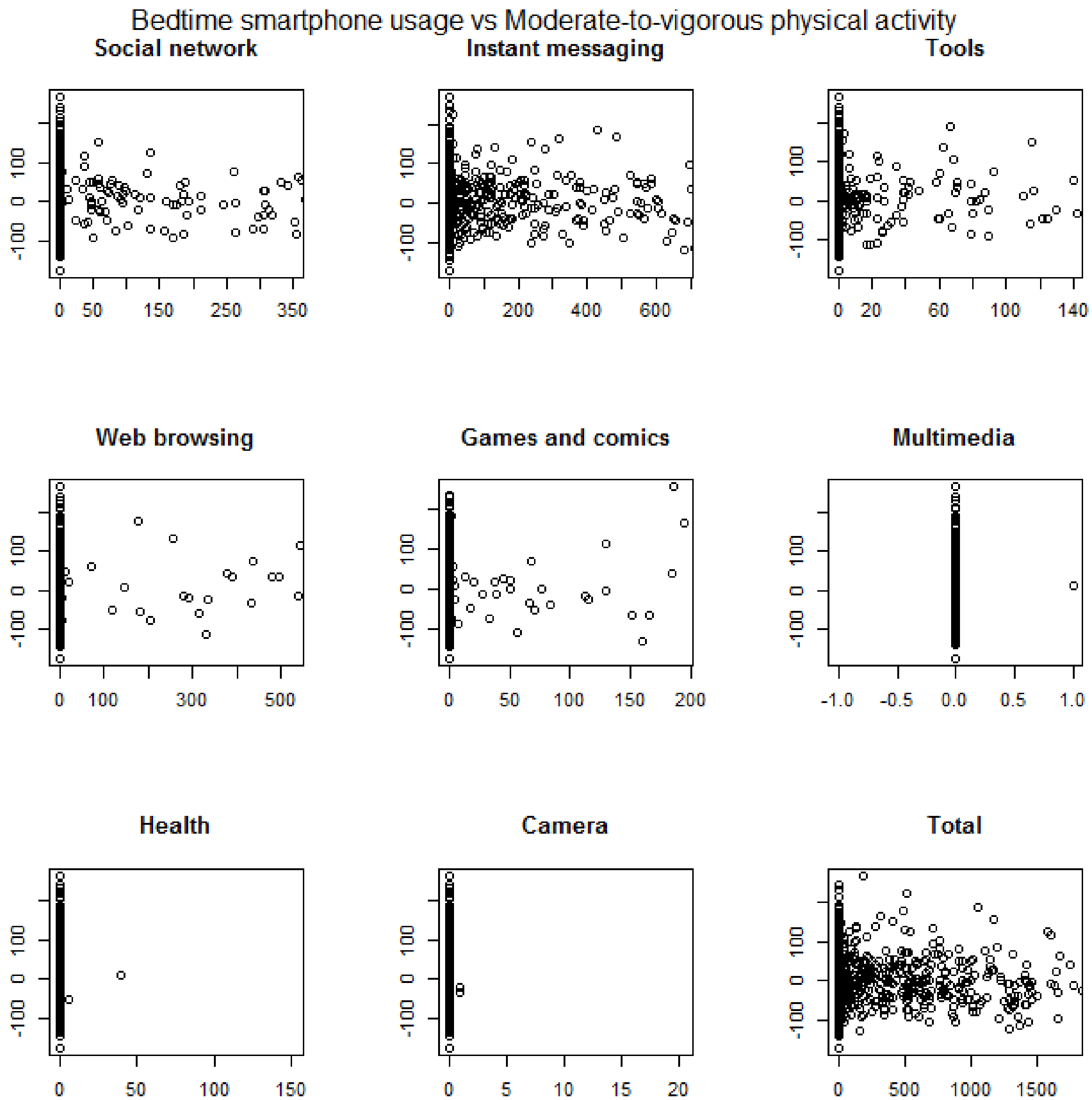

Figure S70. Residual plot of smartphone use during sleep on time spent on moderate-to-vigorous physical activity, overall sample

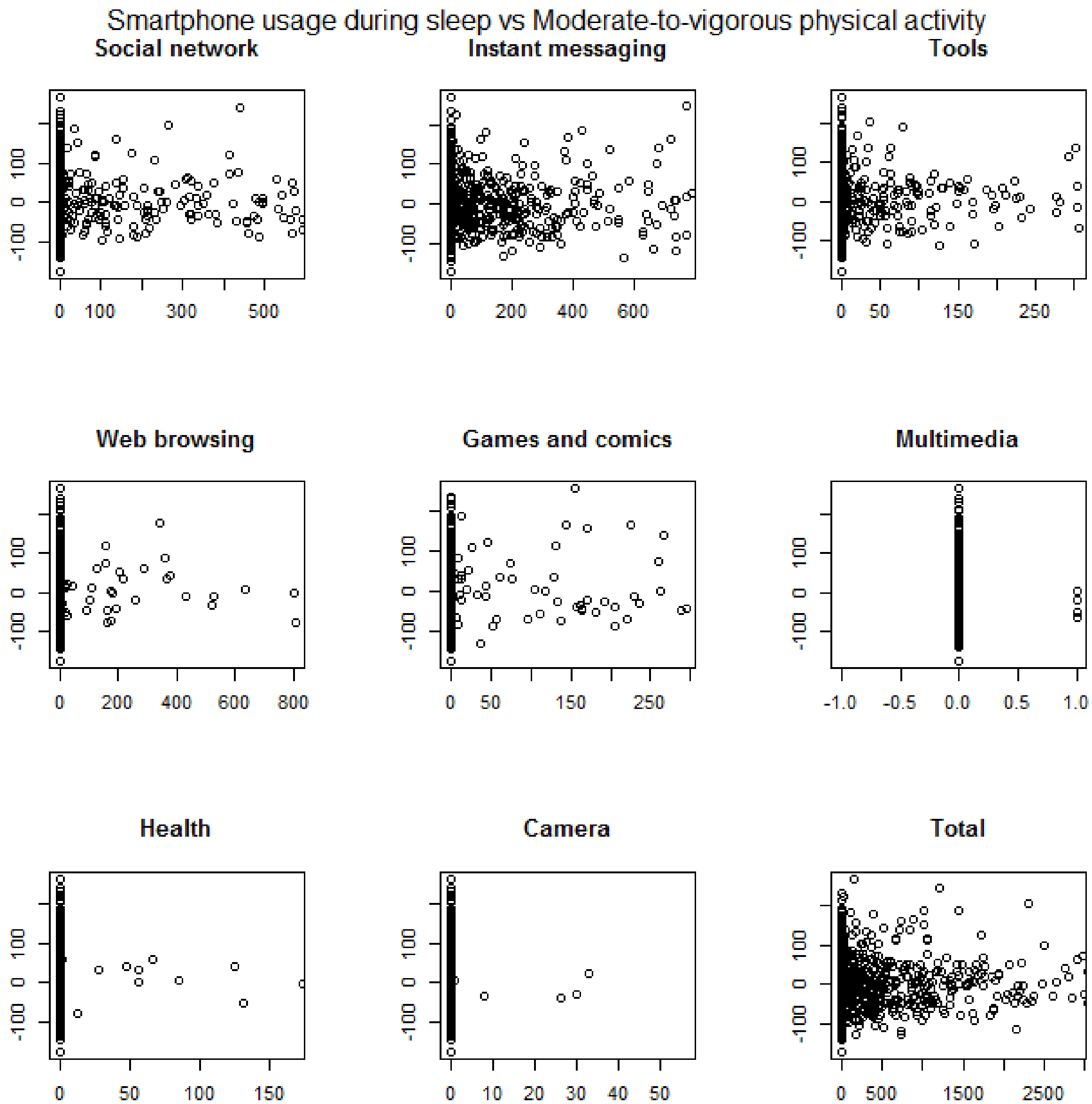

Figure S71. Residual plot of sleep quality on number of steps, overall sample

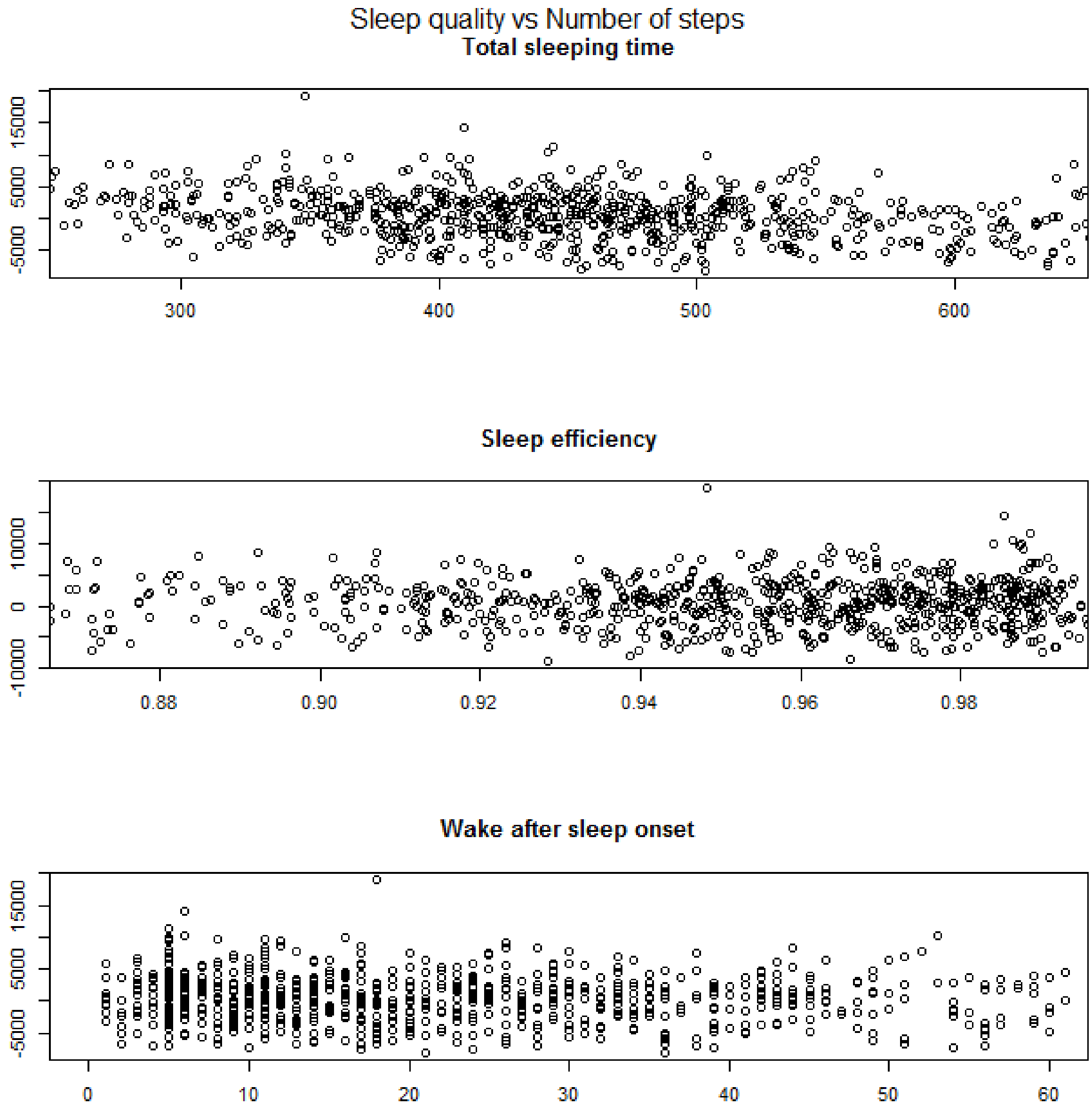

Figure S72. Residual plot of sleep quality on time spent on moderate-to-vigorous physical activity, overall sample

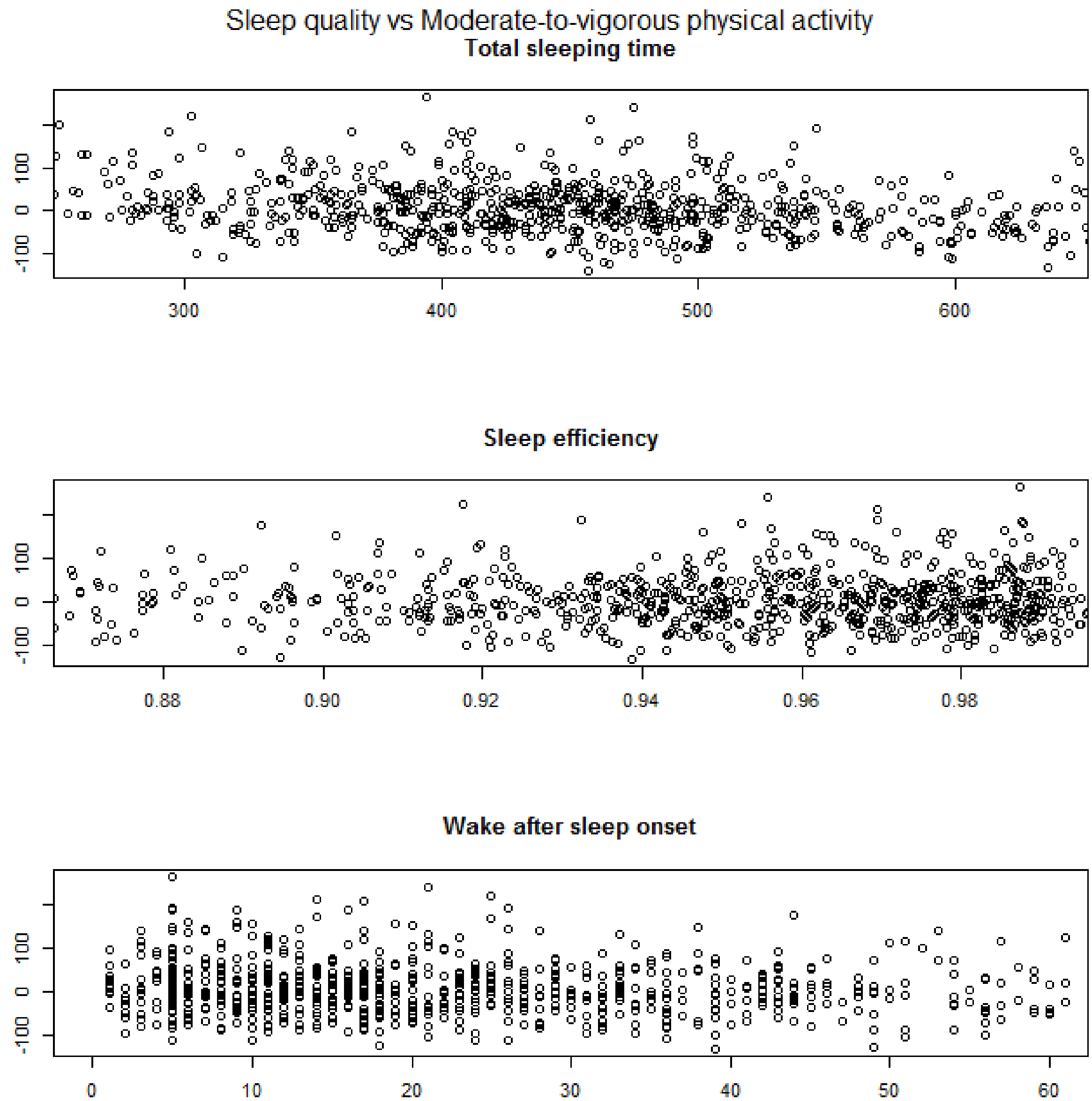

Table S1. Multilevel regression results (intra-class correlation (ICC), auto-correlation, and R^2) of smartphone usage (min) on sleep quality (number of participants=187, number of days=814)

	Secondary school students (number of participants=32, number of days=109)			University students (number of participants=155, number of days=705)			Overall (number of participants=187, number of days=1,106)		
	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)
ICC									
Social network	0.04	0.53	0.40	0.11	0.24	0.24	0.11	0.28	0.26
Instant messaging	0.01	0.55	0.42	0.11	0.25	0.25	0.11	0.28	0.26
Tools	0.07	0.52	0.38	0.12	0.24	0.24	0.11	0.28	0.26
Web browsing	0.03	0.52	0.39	0.11	0.25	0.25	0.10	0.28	0.27
Games and comics	0.07	0.48	0.36	0.12	0.24	0.24	0.11	0.27	0.26
Multimedia	0.05	0.52	0.38	0.12	0.24	0.25	0.11	0.28	0.26
Health	0.05	0.52	0.38	0.11	0.25	0.25	0.11	0.28	0.27
Camera	0.06	0.53	0.42	0.13	0.24	0.25	0.12	0.28	0.27
Total	0.05	0.50	0.38	0.11	0.24	0.25	0.11	0.27	0.26
Auto-correlation									
Social network	-0.01	-0.004	0.01	0.04	0.06	0.08	0.03	0.05	0.07
Instant messaging	0.01	0.02	0.05	0.04	0.06	0.07	0.03	0.05	0.06
Tools	0.01	-0.03	-0.01	0.04	0.06	0.07	0.03	0.05	0.06
Web browsing	0.04	-0.04	-0.02	0.04	0.05	0.07	0.04	0.04	0.06
Games and comics	-0.02	-0.05	-0.01	0.05	0.07	0.08	0.04	0.05	0.06
Multimedia	0.01	-0.03	0.002	0.04	0.06	0.07	0.03	0.05	0.06
Health	0.005	-0.03	0.0003	0.04	0.07	0.08	0.03	0.05	0.07
Camera	-0.02	-0.02	0.02	0.01	0.08	0.08	0.001	0.07	0.07
Total	0.02	-0.02	0.01	0.04	0.07	0.08	0.03	0.05	0.07
R^2									
Social network	0.14	0.60	0.48	0.19	0.35	0.36	0.18	0.39	0.38
Instant messaging	0.08	0.62	0.52	0.19	0.36	0.36	0.18	0.39	0.38
Tools	0.15	0.61	0.49	0.20	0.35	0.36	0.18	0.39	0.38
Web browsing	0.07	0.60	0.48	0.19	0.36	0.37	0.18	0.39	0.38

Games and comics	0.16	0.60	0.48	0.19	0.35	0.36	0.19	0.39	0.38
Multimedia	0.14	0.59	0.47	0.19	0.35	0.36	0.18	0.39	0.37
Health	0.08	0.59	0.47	0.18	0.36	0.36	0.17	0.39	0.38
Camera	0.14	0.62	0.54	0.21	0.36	0.37	0.21	0.39	0.39
Total	0.14	0.62	0.50	0.19	0.36	0.36	0.18	0.39	0.37

Table S2. Multilevel regression results (intra-class correlation (ICC), auto-correlation, and R^2) of smartphone usage (min) on physical activity level (number of participants=187, number of days=1,106)

	Secondary school students (number of participants=32, number of days=176)		University students (number of participants=155, number of days=930)		Overall (number of participants=187, number of days=1,106)	
	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)
ICC						
Social network	0.23	0.30	0.13	0.30	0.15	0.31
Instant messaging	0.20	0.28	0.14	0.30	0.14	0.30
Tools	0.19	0.30	0.14	0.30	0.15	0.30
Web browsing	0.17	0.28	0.15	0.30	0.14	0.31
Games and comics	0.20	0.32	0.14	0.31	0.15	0.31
Multimedia	0.24	0.32	0.14	0.30	0.15	0.31
Health	0.20	0.30	0.14	0.30	0.15	0.30
Camera	0.20	0.29	0.11	0.30	0.14	0.30
Total	0.21	0.32	0.12	0.30	0.14	0.30
Auto-correlation						
Social network	0.34	0.34	0.13	0.12	0.19	0.17
Instant messaging	0.36	0.37	0.14	0.11	0.20	0.17
Tools	0.34	0.34	0.14	0.12	0.20	0.17
Web browsing	0.41	0.39	0.12	0.12	0.21	0.17
Games and comics	0.34	0.32	0.11	0.12	0.20	0.17
Multimedia	0.30	0.31	0.12	0.12	0.19	0.17
Health	0.35	0.34	0.12	0.12	0.20	0.17
Camera	0.35	0.35	0.14	0.11	0.20	0.17
Total	0.34	0.34	0.13	0.11	0.19	0.17
R^2						
Social network	0.35	0.44	0.20	0.40	0.25	0.42
Instant messaging	0.35	0.44	0.19	0.40	0.24	0.42
Tools	0.34	0.45	0.19	0.40	0.24	0.41
Web browsing	0.30	0.44	0.19	0.40	0.24	0.42
Games and comics	0.34	0.46	0.20	0.41	0.24	0.42
Multimedia	0.39	0.47	0.19	0.40	0.25	0.42
Health	0.32	0.44	0.19	0.40	0.24	0.41
Camera	0.32	0.44	0.19	0.40	0.24	0.41
Total	0.36	0.46	0.20	0.40	0.24	0.42

Table S3. Multilevel regression results (intra-class correlation (ICC), auto-correlation, and R^2) of sleep quality on physical activity level (number of participants=352, number of days=1,517)

	Secondary school students (number of participants=123, number of days=459)		University students (number of participants=229, number of days=1,058)		Overall (number of participants=352, number of days=1,517)	
	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)	Number of steps	Moderate-to-vigorous physical activity (min)
ICC						
Total sleeping time (hr)	0.26	0.40	0.05	0.26	0.14	0.36
Sleep efficiency (%)	0.24	0.41	0.06	0.27	0.13	0.36
Wake after sleep onset (min)	0.27	0.42	0.06	0.27	0.14	0.37
Auto-correlation						
Total sleeping time (hr)	0.09	0.35	0.28	0.24	0.21	0.27
Sleep efficiency (%)	0.07	0.28	0.28	0.25	0.20	0.25
Wake after sleep onset (min)	0.07	0.31	0.28	0.25	0.20	0.25
R^2						
Total sleeping time (hr)	0.40	0.54	0.15	0.41	0.27	0.50
Sleep efficiency (%)	0.35	0.54	0.10	0.39	0.22	0.48
Wake after sleep onset (min)	0.38	0.55	0.11	0.39	0.23	0.49

Table S4. Multilevel regression results (intra-class correlation (ICC), auto-correlation, and R^2) of sleep quality on daytime smartphone usage (number of participants=187, number of days=689)

ICC									
Secondary school students (number of participants =32, number of days=92)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	N/A	0.35	N/A	N/A	0.49	N/A	N/A	0.04	0.34
Sleep efficiency (%)	N/A	0.36	N/A	N/A	0.46	N/A	N/A	0.06	0.32
Wake after sleep onset (min)	N/A	0.35	N/A	N/A	0.46	N/A	N/A	0.07	0.31
University students (number of participants =155, number of days=598)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.51	0.16	0.40	0.60	0.34	0.35	0.11	0.02	0.33
Sleep efficiency (%)	0.51	0.16	0.40	0.61	0.35	0.35	0.11	0.02	0.33
Wake after sleep onset (min)	0.51	0.15	0.40	0.61	0.35	0.35	0.11	0.03	0.33
Overall (number of participants	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)

=187, number of days=689)									
Total sleeping time (min)	0.52	0.18	0.36	0.52	0.47	0.25	0.11	0.02	0.34
Sleep efficiency (%)	0.52	0.18	0.36	0.53	0.48	0.25	0.11	0.02	0.34
Wake after sleep onset (min)	0.52	0.17	0.36	0.53	0.47	0.25	0.11	0.02	0.34
Auto-correlation									
Secondary school students (number of participants =32, number of days=92)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.82	0.14	0.30	0.38	0.01	0.42	N/A	0.04	0.21
Sleep efficiency (%)	0.81	0.11	0.31	0.41	-0.005	0.42	N/A	0.04	0.17
Wake after sleep onset (min)	0.81	0.11	0.31	0.37	-0.01	0.41	N/A	0.03	0.17
University students (number of participants =155, number of days=598)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)

Total sleeping time (min)	0.06	0.33	-0.01	0.13	0.37	-0.10	0.26	0.01	0.17
Sleep efficiency (%)	0.06	0.33	-0.02	0.11	0.35	-0.11	0.26	0.002	0.17
Wake after sleep onset (min)	0.06	0.33	-0.02	0.12	0.35	-0.11	0.27	0.002	0.17
Overall (number of participants =187, number of days=689)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.28	0.31	0.05	0.20	0.15	0.13	0.27	0.04	0.19
Sleep efficiency (%)	0.28	0.31	0.04	0.18	0.15	0.13	0.27	0.03	0.19
Wake after sleep onset (min)	0.28	0.31	0.04	0.19	0.14	0.13	0.27	0.03	0.19
R^2									
Secondary school students (number of participants =32, number of days=92)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.003	0.49	0.07	0.03	0.62	0.13	N/A	0.12	0.46
Sleep efficiency (%)	0.03	0.50	0.07	0.003	0.61	0.13	N/A	0.14	0.46

Wake after sleep onset (min)	0.02	0.50	0.07	0.01	0.62	0.14	N/A	0.15	0.46
University students (number of participants =155, number of days=598)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.62	0.27	0.52	0.74	0.53	0.45	0.20	0.04	0.46
Sleep efficiency (%)	0.62	0.27	0.52	0.75	0.54	0.45	0.20	0.05	0.46
Wake after sleep onset (min)	0.62	0.27	0.52	0.74	0.54	0.45	0.19	0.05	0.46
Overall (number of participants =187, number of days=689)	Social network (sec)	Instant messaging (sec)	Tools (sec)	Web browsing (sec)	Games and comics (sec)	Multimedia (sec)	Health (sec)	Camera (sec)	Total (sec)
Total sleeping time (min)	0.67	0.30	0.49	0.68	0.64	0.37	0.19	0.04	0.48
Sleep efficiency (%)	0.67	0.30	0.49	0.69	0.64	0.37	0.19	0.05	0.48
Wake after sleep onset (min)	0.67	0.30	0.49	0.68	0.64	0.37	0.19	0.05	0.48

Table S5. Multilevel regression results (Increment in R^2) of smartphone usage (min) on sleep quality (number of participants=187, number of days=814)

	Secondary school students (number of participants=32, number of days=109)			University students (number of participants=155, number of days=705)			Overall (number of participants=187, number of days=1,106)		
	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)	Total sleeping time (min)	Sleep efficiency (%)	Wake after sleep onset (min)
Increment in R^2									
Social network	6.75%	1.00%	1.33%	0.42%	0.11%	0.06%	0.75%	0.06%	0.06%
Instant messaging	1.43%	3.11%	5.74%	0.08%	0.43%	0.52%	0.07%	0.26%	0.43%
Tools	7.44%	1.74%	2.08%	1.16%	0.01%	0.01%	0.69%	0.08%	0.10%
Web browsing	0.96%	0.84%	0.87%	0.42%	0.75%	1.08%	0.27%	0.63%	0.91%
Games and comics	7.70%	0.98%	1.15%	0.54%	0.04%	0.05%	1.08%	0.01%	0.07%
Multimedia	6.71%	0.44%	0.22%	0.59%	0.19%	0.75%	0.31%	0.01%	0.03%
Health	N/A	N/A	N/A	0.21%	0.71%	0.73%	0.02%	0.62%	0.63%
Camera	6.11%	2.91%	6.81%	2.72%	0.44%	1.21%	2.99%	0.51%	1.53%
Total	5.89%	3.31%	3.14%	0.16%	0.28%	0.34%	0.52%	0.02%	0.02%