Nature and Science of Sleep

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ORIGINAL RESEARCH

# The Relationship Between Digital Activity and Bedtime, Sleep Duration, and Sleep Quality in Chinese Working Youth

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**Purpose:** The study aims to examine whether and how digital activities influence sleep issues among working Chinese youth.

**Methods:** This study used data from the China Family Panel Studies (CFPS) a Chinese population-based survey, and employed the multilevel ordinal logistic regression model (MOLRM) to test the associations between digital engagement (whether to engage in digital activity, frequency, and duration) and sleep issues (bedtime, sleep duration, and quality) among Chinese working youth. Additionally, the restricted cubic spline model (RCSM) was adopted to fit the MOLRM to evaluate the nonlinear relationship between digital activity duration and sleep quality, and thus determine the optimal range of digital activity duration.

**Results:** The analysis included 7849 working young adults. The digital usage rate was 84.11%. Digital use was not significantly associated with average, workday, or free-day sleep duration, after controlling for all potential confounders. However, most digital activity indicators could significantly predict bedtime and sleep quality. Furthermore, the RCSM indicated a non-linear relationship pattern between digital activity duration and sleep quality, with a weekly peak point of 25 h. Age significantly moderated the relationship between digital activity, sleep duration and bedtime. Younger youth who used digital media more frequently and for a longer time tended to sleep later and had shorter sleep duration than older youth.

**Conclusion:** Digital usage significantly predicted later bedtime among Chinese working youth; however, it was not linked with sleep duration on workdays or free days. In parallel, a nonlinear correlation between digital activity duration and sleep quality indicated that appropriate digital activity duration (less than 25 h weekly) may contribute to good sleep quality.

**Keywords:** working youth, digital activity, sleep issues, time shifting, time displacement

## Introduction

Since the beginning of the 21st century, especially with the popularization of mobile Internet, digital construction and technology development have presented an unprecedented landscape in China, changing everyone's daily lifestyle and behavioral habits, including sleep. According to "2020 Sleemon Chinese Sleep Index Report", the average bedtime of people in China was delayed from 22:00 in 2013 to 23:55 in 2019, and the average sleep duration was 6.92 h, which was 1.58 h less than that in 2013.[1] During the COVID-19, this phenomenon tended to deteriorate and people went to bed two or three hours later overall.[2] In parallel, the online weekly duration (how many hours one person spent on the Internet per week) generally increased from 25 h in 2013 to 27.6 h in 2018 (CNNIC, 2019),[3] and 20:00–23:00 was one of the most active time periods, extending to approximately 02:00 in the morning for young adults.[4] Advancement in technology including artificial lighting, TV, computer, Internet, smartphone and other electronic devices based on screen was a major cause of late bedtime and short sleep duration.[5] It is therefore logical to infer that digitization is an important incentive to accelerate the advent of the era characterized by going to bed late and a short duration of sleep.

The pace of youth life and work is gradually accelerating with the popularization of computers and smartphones, and time is a scarce resource for them, with a high prevalence of insufficient sleep. The increased prevalence of sleep



Received: 16 November 2021
Accepted: 6 March 2022
Published: 14 March 2022

epidemics in working youth is a major health concern as late bedtime, short sleep duration, and poor sleep quality have been associated with an increased risk of physical and mental diseases, such as obesity,[6,7] type 2 diabetes,[8] depression,[9,10] poor work performances,[11–13] unethical and high-risk behaviors[14–16] low life satisfaction and well-being,[17] increasing all-cause mortality.[18] The high prevalence of youth sleep problems (e g insomnia, delayed sleep onset, poor sleep) with the rapid pace of advanced technology, necessitates research on more recent factors that might affect unhealthy sleep status, such as excessive new technology use.

The pervasive influence of online activities on sleep status gained increasing attention from academics and practitioners over the past decade. Many previous studies reported that the recent proliferation of the Internet, especially mobile internet, and portable smart devices, created a society called "Permanently Online and Permanently Connected," and significantly affected youth sleep.[5,19–21] As mentioned above, the online duration increased 2.6 h per week from 2013 to 2018 while the sleep duration decreased by 1.58 h in China. Therefore, it is vital to identify the essence and characteristics of their relationship in youth.

Based on the existing literature, most relevant to the current study, three mechanisms were proposed to explain the association between online behaviors and sleep issues: bedtime, sleep duration, and sleep quality. First, screen light theory refers to exposure to light emitted by an electronic screen that interferes with the secretion of melatonin, delays sleep onset, and disrupts sleep quality.[22,23] This theory is rooted in the non-visual effects of light and is explained as a physiological mechanism, which is the most consistent explanation. Notably, the effect of screen light on melatonin secretion and the circadian system has a cumulative effect over time; thus, a detrimental effect would occur only when the uninterrupted online duration lasts more than 2 h.[24] Second, time shifting hypothesis was proposed by Custers and Van den Bulck (2012) to explain the phenomenon that media use in the bedroom predicts later bedtime and later rise time, thus keeping the total sleep duration unchanged, which appears to be more suitable to college students and those adults with a flexible timetable.[25] Tavernier and Willoughby (2014) collected the data of 942 college students' sleep duration, sleep problems, television watching and online social network use and found no association between TV or social media use and sleep duration, supporting time shifting hypothesis.[26] Similarly, a few studies based on general adults also found pre-sleep media use could not independently predict shorter sleep duration.[23,27] The third mechanism is time displacement, a process whereby media use delays going to sleep and thus shortened sleep duration.[27,28] Specifically, media use is an activity without strict and predefined limits of time and space; therefore it is more likely for people to unconsciously engage in it for a long time, thereby delaying the bedtime if this behavior happens late in the day or is part of a bedtime ritual. However, the majority of these studies were conducted on children and adolescents which may not be adaptable for adults since adolescents must wake up the next morning due to the school schedule or parents' requirements.[23] Although the studies mentioned above have controversial results regarding the impact of media use on sleep duration, they all concur that media use could delay bedtime and thus impair sleep quality. Following a series of early studies focused on sleep quantity, more recent studies have explored sleep quality independently[29–31] and certain electronic media (e g social media),[32–34] with samples still concentrating on adolescents and undergraduates.

Although the association between Internet use and sleep are continually referenced in both the literature and the popular press, there are several limitations. Firstly, the majority of research investigating this link are focused on children, adolescents,[5,35–37] college students,[26,38,39] with few conducted on the general young adults[40] or working youth,[5] The popularity of electronic instruments among the latter are higher and they are also more vulnerable and susceptible to sleep epidemics than any other age groups, currently.[29,41] Additionally, the related studies suggested that different links and mechanisms are at work among adults, and young adults may use digital media as a coping mechanism to manage sleep problems.[26] More importantly, the work schedule of "996" "007" is common in China. These are two typical work systems which refer to "employees work more than 10 hours, six days a week, starting at 9:00 am and ending at 9:00 pm, and taking one hour or less off at noon and evening" and "employees work from zero to zero, seven days a week", respectively. Almost all youth work longer than the required eight hours per day. As the chief users of high technology products and services than any other age groups, working youth in China will not receive enough attention to the influences of Internet on their sleep problems. Secondly, studies investigated the correlation between Internet/media use and treated digital activities as comprehensive, however, disregarded the multidimensional nature of online activities. Most research focused only on social media use which is an element of digital activities. Exelmans and

Scott (2019) pointed out that users spend less of their spare time using social media, however they may mindlessly spend much more time browsing the web than they expected.[30] Thirdly, the majority of literature only examines online activities before going to bed or pre-sleep,[42,43] and ignore the function of daily online behaviors, which also occur in working youth.[44] Surfing the Internet in the morning or afternoon may reduce the time that you should be working, thus delaying work until the evening and increasing the chance of staying up late. Studies have shown that the depletion of self-regulating resources is continuous throughout the day.[45]

In summary, given the gradually disadvantaged sleep status of working Chinese youth and the paucity of research on the impact of digital activities on sleep quantity and quality, there is a strong need to understand the associations between digital activities and sleep duration, bedtime, and/or sleep quality. The current study aimed to fill this gap by examining whether and how digital activities influence sleep issues among working Chinese youth. Additionally, further analysis of the frequency and types of digital activities can provide a deep understanding of the complexity and variety of technological developments, which may help inform digital behavior habits to reduce the risk of sleep disorders.

# Materials and Methods

## Data Source

The data were retrieved from the China Family Panel Studies (CFPS) which was funded by Peking University and conducted by the Institute of Social Science Survey (ISSS). The CFPS is a nationally representative, ongoing, open longitudinal study on individual-, family-, and community-level information in China which was approved by the ISSS of Peking University and launched in 2010. All participants provided written informed consent prior to participating in the survey. The CFPS recruited approximately 15,000 households using a multistage probability proportional-to-size sampling method. Data covered 37,147 Chinese individuals who resided in 621 villages/communities from 25 provinces, and represented 95% of the Chinese population. Detailed information about CFPS, excluding all privately identifiable information, was accessed from http://www.isss.pku.edu.cn/cfps/en/data/public/index.htm (accessed on 15 January 2021).

The All-China Youth Federation defines youth as individuals aged 18–44 years.[46] According to the CFPS questionnaire and Chinese working youth research,[47] we selected participants aged 18–44 years who completed the survey in 2018. Our final analytical sample consisted of 7849 respondents, after eliminating key variables with missing values.

## Measurements

### Sleep Issues

In the 2018 CFPS, sleep issues were measured using the following three indicators: sleep duration, bedtime, and self-rated sleep quality. Three items on sleep duration were constructed from relevant survey questions, including "On average, how many hours do you sleep each day?", "On a typical workday, how many hours do you sleep?" On a typical free day, how many hours do you sleep?" In the original dataset, if participants reported the first question, the latter two would be missing; conversely, the first one would be lacking. Thus, sleep duration was calculated using the equation (workday × 5 + free-day × 2)/7 and was categorized as short sleep duration (<7h), normal sleep duration (7–9h), and long sleep duration (>9h), which proved to be useful in Chinese samples.[48,49]

Bedtime was assessed using the item "What time do you go to bed?." To obtain a metric variable, hours were counted from 0 to 24, and hours after midnight were counted as 25 (for 1:00), 26 (for 2:00), etc;[24] and thereafter converted to decimal form (ie 21:30 was 9.50).[50] According to Druiven et al, bedtime was categorized into three levels based on quintile, especially, the 1st quintile was encoded as "early bedtime", the 2nd, 3rd and 4th quintile were encoded as "normal bedtime", and the 5th quintile was encoded as "late bedtime".[51]

Self-rated sleep quality was assessed by "How do you assess the quality of your sleep during the previous month (good, fair, constantly poor, or mostly poor)?." This variable was an ordinal category variable, with higher values indicating higher sleep quality. We encoded this in reverse.

### Digital Activities

Digital activities included four parts. First, digital usage was measured by the item, "Did you ever use the cellphone and/ or computer to access the Internet?" and is a binary variable. Second, type of digital activities was assessed by five questions "How often do you use the Internet to do these activities? Learn/work/sociality/entertainment/shopping". Third, the frequency of digital activities was calculated as the sum of the five activities mentioned above. Fourth, duration of digital activities was assessed based on the respondents' answer to the question "How many hours do you spend on the Internet in a week of spare time generally?" This was a continuous variable.

### Covariates

The potential covariates were based on existing literature and included three categories. The first category included demographic information and socioeconomic variables, such as age, gender, residential address (urban=1 or rural=0), marital status (married=1), annual household income (log-transformed), and educational level (primary school or lower = 1; middle school = 2; high school = 3; college and higher = 4). The second category was health-related information, including BMI [weight (kg)/height (m)$^2$], self-rated health status (poor=1, fair=2, good=3), presence of chronic diseases (yes=1), and the CESD store. Finally, variables about individuals' lifestyle included drinking (yes=1), smoking (yes=1), physical exercise (yes=1), and nap (yes=1).

The descriptions of all above variables is reported in Table S1.

## Statistical Strategy

First, the mean and standard deviation for continuous variables and percentages for categorical variables were used to describe the sample characteristics. Differences in key variables were calculated using the chi-square test. Second, the data structure of the CFPS was nested with individuals nested within family, and Dahland El-Sheik (2007) pointed out that sleep interplayed with family environment, family members, family relationships, and other family background factors, and the data of those observations employed from one family were non-independent.[52] Additionally, the intra-class correlation coefficient (ICC) was used to test the applicability of multilevel modelling, and the results indicated the necessity of this model (see Table S3). Since the outcome measures analyzed were ordinally categorical variables, the associations between digital activities and sleep issues were applicable to multilevel ordinal logistic regression models (MOLRM). Odds ratios (ORs) and 95% confidence intervals (CIs) were used to describe the association between the results and explanatory variables, and other covariates were uncontrolled and controlled separately. Third, to explore the duration of digital activities that contribute to optimal sleep, the 4-node restricted cubic spline model was used to fit the multilevel logistic regression model to evaluate the nonlinear relationship between digital activity duration and sleep quality, and thus determine the optimal range of digital activity duration. Restricted cubic spline analysis could reduce the risk of information defects and result in bias caused by researchers' subjective classification, compared with categorized regression and quantile regression.[53]

Thereafter we conducted two sets of sensitivity analyses to confirm robustness. First, we operationalized bedtime and sleep quality as continuous for all digital activity indices. Thereafter, we entered five types of digital activities: learning, working, socialization, entertainment, and shopping into all multilevel models as dichotomous predictor variables for all sleep indicators.

All statistical tests were two-sided, and $p < 0.05$ was considered statistically significant. Statistical analyses were performed using SPSS (version 26.0; SPSS, Inc., Chicago, IL, USA) and STATA 16.0 (STATA Corporation, College Station, TX, USA).

# Results

## Descriptive Statistics

A total of 7849 working young adults were enrolled; the descriptive results are presented in Table S1. The proportion of working youth who used computers and/or cell phones to access the Internet was 84.11%. Table 1 shows the results of key descriptive statistics and intergroup difference tests in terms of digital usage. Initially, Chinese working youth's average sleep duration was 7.84–7.92 h, which was within the recommended sleep duration standard (7–9 h).[48,49] Significant differences were observed in sleep duration, bedtime, and sleep quality between digital users and non-users, and there were similar significant differences in frequency, duration, and types of digital activities (see Table S2). Moreover, average sleep duration (7.84 h±1.12h) and workday sleep duration (7.60h±1.20h) in digital users were shorter than non-digital users (7.92h±1.30h, 7.77h±1.42h, respectively), while the result of free-day sleep duration was opposite (8.41 h > 8.26 h). Additionally, a higher proportion of late bedtime (21.49%) and poor sleep quality (16.44%) were observed among digital users.

**Table 1** Participants' Sleep Issues and Univariate Analysis

| Variables | Digital Usage | | $\chi^2$/F | *p* |
|---|---|---|---|---|
| | No (N=1247) | Yes (N=6602) | | |
| Average sleep duration[a] | 7.92 (1.30) | 7.84 (1.12) | 4.996 | 0.025 |
| Workday sleep duration[a] | 7.77 (1.42) | 7.60 (1.20) | 19.823 | <0.001 |
| Free-day sleep duration[a] | 8.26 (1.53) | 8.41 (1.48) | 10.788 | 0.001 |
| Average sleep duration[b] | | | | |
| Short | 348 (27.91) | 1696 (25.69) | 40.809 | <0.001 |
| Normal | 652 (52.29) | 4001 (60.60) | | |
| Long | 247 (19.81) | 905 (13.71) | | |
| Workday sleep duration[b] | | | | |
| Short | 444 (35.61) | 2759 (41.79) | 45.697 | <0.001 |
| Normal | 559 (44.83) | 3004 (45.50) | | |
| Long | 244 (19.57) | 839 (12.71) | | |
| Free-day sleep duration[b] | | | | |
| Short | 303 (24.30) | 1467 (22.22) | 8.254 | 0.016 |
| Normal | 528 (42.34) | 2654 (40.20) | | |
| Long | 416 (33.37) | 2481 (37.58) | | |
| Bedtime[b] | | | | |
| Early | 851 (68.24) | 2729 (41.36) | 312.996 | <0.001 |
| Normal | 284 (22.77) | 2454 (37.17) | | |
| Late | 112 (8.98) | 1419 (21.49) | | |
| Sleep quality[b] | | | | |
| Mostly poor | 63 (5.05) | 291 (4.41) | 16.872 | 0.001 |
| Constantly poor | 113 (9.06) | 794 (12.03) | | |
| Fair | 403 (32.32) | 2318 (35.11) | | |
| Good | 668 (53.57) | 3199 (48.46) | | |

**Notes**: [a]This variable was computed as a continuous variable, data were presented as the means (standard deviation: S.D.); [b]This variable was computed as a categorical variable, data were presented as the number (the percent of each category: %).

Table 2 shows the correlation results of the key variables. The observed relationships between digital activity indices and sleep variables were significantly positive, which may preliminarily confirm the relationship between them.

## Association Between Sleep Duration and Digital Activities

First, we included digital usage, frequency, duration, and type of digital activities to predict sleep duration. Table 3 displays the multilevel ordinal logistic regression results for the unadjusted and adjusted control variables. The

**Table 2** Correlation Coefficient Matrix

| | Average Sleep Duration | Workday Sleep Duration | Free-Day Sleep Duration | Bedtime | Sleep Quality | Digital Usage | Frequency of Digital Activities | Digital Activities Duration |
|---|---|---|---|---|---|---|---|---|
| Average sleep duration | 1 | | | | | | | |
| Workday sleep duration | 0.821*** | 1 | | | | | | |
| Free-day sleep duration | 0.696*** | 0.476*** | 1 | | | | | |
| Bedtime | −0.158*** | −0.225*** | −0.063*** | 1 | | | | |
| Sleep quality | 0.098*** | 0.110*** | 0.074*** | −0.106*** | 1 | | | |
| Digital usage | −0.023** | −0.069*** | 0.030*** | 0.189*** | −0.030*** | 1 | | |
| Frequency of digital activities | −0.022** | −0.099*** | 0.054*** | 0.289*** | −0.024** | 0.744*** | 1 | |
| Digital activities duration | 0.014 | −0.039*** | 0.061*** | 0.208*** | −0.035*** | 0.443*** | 0.455*** | 1 |

**Notes**: Bivariate Pearson (for continuous data) and Spearman rho (for categorical data) correlation analyses were conducted. **$p$<0.01, ***$p$<0.001.


https://doi.org/10.2147/NSS.S348929

**Table 3** The Multilevel Ordinal Logistic Regression of Digital Activities and Sleep Duration Groups for the Average, Workday and Free-Day

| | **Average Sleep Duration** | | | | **Workday Sleep Duration** | | | | **Free-Day Sleep Duration** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **M1** | | **M2** | | **M3** | | **M4** | | **M5** | | **M6** | |
| | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** |
| **Digital usage** (ref: no) | | | | | | | | | | | | |
| Yes | 0.887 [0.777, 1.012] | 0.075 | 0.911 [0.786, 1.056] | 0.786 | 0.691*** [0.608, 0.786] | <0.001 | 0.856* [0.742, 0.987] | 0.032 | 1.189** [1.048, 1.349] | 0.007 | 1.002 [0.870, 1.153] | 0.978 |
| **Frequency** | 0.996 [0.991, 1.001] | 0.132 | 1.000 [0.994, 1.007] | 0.914 | 0.980*** [0.975, 0.985] | <0.001 | 0.992* [0.985, 0.998] | 0.012 | 1.012*** [1.007, 1.017] | <0.001 | 1.006 [0.999, 1.012] | 0.085 |
| **Digital activities duration** | 1.002* [0.998, 1.006] | 0.232 | 1.001 [0.997, 1.005] | 0.717 | 0.993** [0.989, 0.997] | 0.001 | 0.996 [0.992, 1.000] | 0.071 | 1.011*** [1.007, 1.015] | <0.001 | 1.005* [1.001, 1.009] | 0.021 |
| **Age*Frequency** | 0.998*** [0.997, 0.998] | <0.001 | 0.999** [0.998, 1.000] | 0.007 | 0.998*** [0.998, 0.999] | <0.001 | 0.999 [0.998, 1.000] | 0.054 | 0.997*** [0.997, 0.998] | <0.001 | 0.998*** [0.997, 0.999] | <0.001 |
| **Age*Duration** | 0.998*** [0.997, 0.998] | <0.001 | 0.999*** [0.998, 1.000] | <0.001 | 0.998*** [0.998, 0.999] | <0.001 | 0.999* [0.999, 1.000] | 0.011 | 0.997*** [0.997, 0.998] | <0.001 | 0.999*** [0.998, 0.999] | <0.001 |
| **Frequency of each digital activity** | | | | | | | | | | | | |
| Learning | 0.988* [0.962, 1.000] | 0.046 | 0.996 [0.974, 1.019] | 0.740 | 0.938*** [0.920, 0.956] | <0.001 | 0.981 [0.959, 1.003] | 0.095 | 1.015 [0.996, 1.034] | 0.122 | 0.990 [0.968, 1.012] | 0.365 |
| Working | 0.981* [0.965, 0.998] | 0.029 | 1.007 [0.985, 1.030] | 0.533 | 0.932*** [0.916, 0.947] | <0.001 | 0.979 [0.959, 1.001] | 0.059 | 1.034*** [1.017, 1.051] | <0.001 | 1.025* [1.003, 1.047] | 0.025 |
| Socialization | 0.992 [0.972, 1.013] | 0.447 | 0.991 [0.969, 1.015] | 0.460 | 0.942*** [0.924, 0.961] | <0.001 | 0.969** [0.947, 0.991] | 0.006 | 1.038*** [1.018, 1.059] | <0.001 | 1.002 [0.980, 1.025] | 0.841 |
| Entertainment | 1.011 [0.999, 1.032] | 0.297 | 1.014 [0.999, 1.037] | 0.254 | 0.959** [0.940, 0.979] | <0.001 | 0.990 [0.968, 1.013] | 0.401 | 1.066*** [1.045, 1.087] | <0.001 | 1.038** [1.015, 1.062] | 0.001 |
| Shopping | 0.980 [0.958, 1.002] | 0.077 | 0.995 [0.969, 1.021] | 0.691 | 0.931*** [0.911, 0.952] | <0.001 | 0.982 [0.957, 1.008] | 0.165 | 1.040*** [1.018, 1.063] | <0.001 | 1.015 [0.989, 1.041] | 0.274 |

**Notes**: The results were quantified by OR, with a confidence interval in square brackets. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. M1, M3, and M5 were unadjusted models only including independent variables. M2, M4, and M6 were adjusted models, adjusted for demographic, socioeconomic, health-related, and lifestyle variables.
**Abbreviations**: CI, confidence interval; OR, odds ratio.

association between any of the digital activity variables and average sleep duration for the adjusted models was not significant (see Table 3, M2). In addition to average sleep duration, we conducted the models for workdays and free days, and found complex correlations between them after controlling for all covariates (see Table 3, M4, and M6). Compared to those working youth with a lower frequency of digital activity, especially socialization, those who often chatted using the Internet had a shorter sleep duration than during workday nights (OR=0.969, 95% CI= [0.947, 0.991], *p*=0.006). In contrast, respondents with longer online work (OR = 1.025, 95% CI = [1.003, 1.047], *p* =0.025) and entertainment (OR = 1.038, 95% CI = [1.015, 1.062], *p* =0.001) times were more likely to sleep longer. In other words, they spent more time on some digital activities, less time sleeping during workdays, and more time sleeping during the free day. A potential explanation is that there was no strict time schedule on the free day, and young people tended to spend more time surfing the Internet and sleeping.

There was a strong correlation between digital usage and age, therefore two interaction terms (digital activity frequency * age, digital activity duration * age) were entered into the analyses (see Table 3). Although there was no direct relationship between digital activity variables and sleep duration, the interactions between digital frequency and age predicting average (OR=0.999, 95% CI= [1.010,1.008], *p*<0.001) and free-day (OR=0.998, 95% CI= [0.997, 999], *p*<0.001) sleep duration were significant. Workday sleep duration was marginally significant (OR=0.999, 95% CI= [0.998,1.000], *p*=0.054). Duration of digital activity showed similar results. Furthermore, working youth who engaged in digital activity frequently slept less than those with lower frequency as age increased.

## The Association Between Bedtime and Digital Activities

We adopted multilevel ordinal logistic regression models using all digital activity variables as predictor factors and bedtime as outcomes. The results in Table 4 show that all the series of indicators of digital activities could positively predict respondents' bedtime. After controlling all covariates, compared with the non-digital users, those who frequently engaged in digital usage were more likely to sleep late (OR=1.036, 95% CI= [1.028, 1.045], *p*<0.001), like those who had longer digital activities duration (OR=1.022, 95% CI= [1.017, 1.028], *p*<0.001). The results of the impacts among five different digital activities reported that learning (OR=1.038, 95% CI= [1.011, 1.066], *p*=0.006), working (OR=1.079, 95% CI= [1.051, 1.107], *p*<0.001), socialization (OR=1.114, 95% CI= [1.083, 1.147], *p*<0.001), entertainment (OR=1.085, 95% CI= [1.054, 1.116], *p*<0.001) and shopping (OR=1.139, 95% CI= [1.104, 1.175], *p*<0.001) were significantly associated with bedtime.

Similarly, we analyzed the role of age in the relationship between digital activity variables and bedtime. The results in Table 4 suggest that although the interaction between age and digital frequency predicting bedtime was not significant, age significantly moderated the association between digital activity duration and bedtime (OR=1.001, 95% CI= [1.000,1.002], *p*=0.002).

## The Association Between Sleep Quality and Digital Activities

In addition to objective sleep indicators, we analyzed working youths' subjective evaluations of their sleep quality. Similar to bedtime, the results of multilevel ordinal logistic regression models (see Table 4) show that there were significant negative relationships between the series of indicators of digital activity and sleep quality in both the unadjusted (M9) and adjusted (M10) models. Among those respondents who engaged in digital activity, frequency (OR=0.978, 95% CI= [0.973, 0.984], *p*<0.001) and duration (OR=0.993, 95% CI= [0.989, 0.998], *p*<0.001) of digital activities could negatively predict sleep quality. Additionally, significant relationships were observed between the type of digital activity and sleep quality. Specifically, the higher the frequency of every digital activity, the higher the incidence of poor sleep quality (see Table 4, M10, raw 9–13). We also analyzed the role of age in the relationship between digital activity variables and sleep quality. The results in Table 4 suggest that although there were significant relationships between digital behavior indices and sleep quality, age did not significantly moderate the association between the frequency, duration of digital activity, and sleep quality.

Since the duration of digital activity was a continuous variable and there was a non-linear relationship between digital activity duration and sleep quality, the restricted cubic spline (RCS) was adopted to fit and visualize them (see Figure 1) to obtain the duration range with optimal sleep quality. On average, digital activity duration negatively affected sleep


https://doi.org/10.2147/NSS.S348929

**Table 4** The Multilevel Ordinal Logistic Regression for Bedtime and Sleep Quality

| | **Bedtime** | | | | **Sleep Quality** | | | |
|---|---|---|---|---|---|---|---|---|
| | **M 7** | | **M 8** | | **M 9** | | **M 10** | |
| | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** | **OR [95% CI]** | ***p*** |
| **Digital usage** (ref: no) | | | | | | | | |
| Yes | 4.053***[3.385, 4.852] | <0.001 | 1.655***[1.374, 1.993] | <0.001 | 0.825**[0.726, 0.936] | 0.003 | 0.685***[0.590, 0.794] | <0.001 |
| **Frequency** | 1.082*** [1.075, 1.090] | <0.001 | 1.036***[1.028, 1.045] | <0.001 | 0.993**[0.988, 0.998] | 0.006 | 0.978***[0.973, 0.984] | <0.001 |
| **Digital activities duration** | 1.045*** [1.040, 1.051] | <0.001 | 1.022***[1.017, 1.028] | <0.001 | 0.995*[0.991, 0.999] | 0.012 | 0.993**[0.989, 0.998] | 0.002 |
| **Age*Frequency** | 0.999***[0.998, 0.999] | <0.001 | 1.001[1.000, 1.002] | 0.202 | 0.999***[0.999, 1.000] | <0.001 | 1.000[1.000, 1.001] | 0.324 |
| **Age*Duration** | 0.999***[0.998, 0.999] | <0.001 | 1.001**[1.000, 1.002] | 0.002 | 1.000*[0.999, 1.000] | 0.018 | 1.000[0.999, 1.001] | 0.817 |
| **Frequency of each digital activity** | | | | | | | | |
| Learning | 1.205***[1.177, 1.235] | <0.001 | 1.038**[1.011, 1.066] | 0.006 | 0.993[0.975, 1.012] | 0.457 | 0.967**[0.945, 0.989] | 0.004 |
| Working | 1.247***[1.221, 1.275] | <0.001 | 1.079***[1.051, 1.107] | <0.001 | 0.982*[0.966, 0.999] | 0.033 | 0.949***[0.928, 0.970] | <0.001 |
| Socialization | 1.281***[1.247, 1.317] | <0.001 | 1.114***[1.083, 1.147] | <0.001 | 0.980*[0.960, 0.999] | 0.039 | 0.944***[0.922, 0.966] | <0.001 |
| Entertainment | 1.257***[1.224, 1.292] | <0.001 | 1.085***[1.054, 1.116] | <0.001 | 0.981[0.962, 1.001] | 0.062 | 0.948***[0.926, 0.971] | <0.001 |
| Shopping | 1.339***[1.301, 1.377] | <0.001 | 1.139***[1.104, 1.175] | <0.001 | 0.956***[0.936, 0.977] | <0.001 | 0.924***[0.900, 0.949] | <0.001 |

**Notes**: The results were quantified by OR, with a confidence interval in square brackets. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. M7, M9 were unadjusted models only including independent variables. M8, M10 were adjusted models, adjusted for demographic, socioeconomic, health-related, and lifestyle variables.
**Abbreviations**: CI, confidence interval; OR, odds ratio.


https://doi.org/10.2147/NSS.S348929

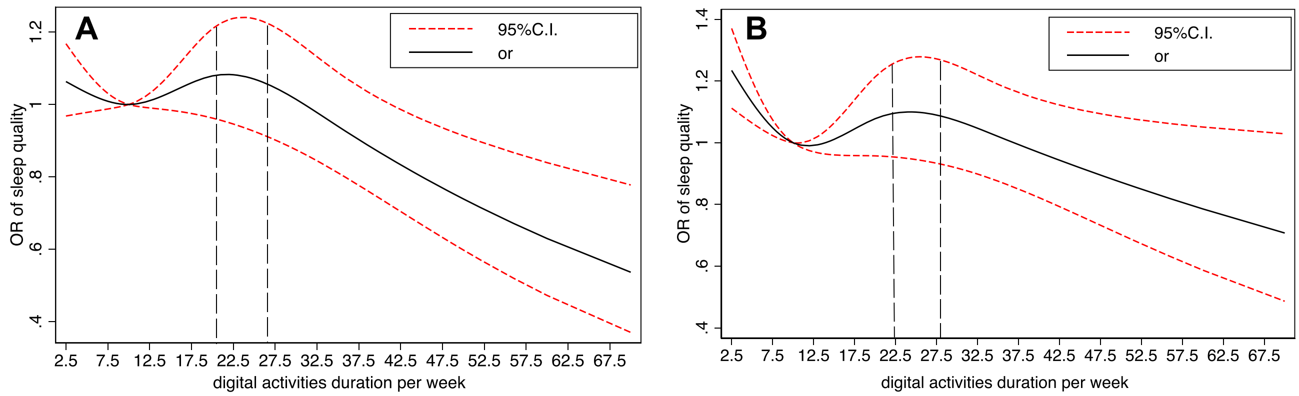


**Figure 1** The digital activities duration and sleep quality.
**Notes**: (**A**) before adjustment of confounding factors; (**B**) after adjustment of demographic, socioeconomic, health-related, and lifestyle variables.
**Abbreviation**: OR, odds ratio.

duration, however proper digital activity (approximately 20–25 h per week, see Figure 1A) showed increasing trends and decreased after the peak point. Similar to unadjusted condition, the results of the RCS with all potential confounders controlled (see Figure 1B), the relationship between digital activity duration and sleep quality reflected an inverted U-shaped curve after the reference value of 10h, with the peak point locating 22.5–27.5 h. Therefore, when digital activity duration was less than approximately 25 h per week, sleep quality increased.

## Sensitivity Analysis

Tables S4 and S5 show the results of the sensitivity analyses conducted to confirm the robustness of our results. The digital activity frequency, duration, and frequency of each digital activity were negatively related to sleep quality (Table S4). Similarly, whether to engage in online learning, working, socialization, entertainment, or shopping was not associated with sleep duration on average, workdays and free-days, however it significantly predicted later bedtime and worse sleep quality. Therefore, the results of the sensitivity analyses support the robustness of our conclusions after adjusting for all covariates.

# Discussions

Internet and technological devices are a vital part of our daily life, especially for young adults, with a 65.9% prevalence among all Chinese Internet users.[3] In parallel, the prevalence of sleep problems among youth has increased recently, including later bedtime, shorter sleep duration and poor sleep quality. Technology development and use is one of the risk factors. Taken together, the current study evaluated whether and how digital activities and habits affect sleep duration, bedtime, and sleep quality among Chinese youth. Young working people were the target sample, as they were the core users of technological instruments, whether at work or in daily life.

First, descriptive characteristics and exploratory correlations between all key variables in this sample are presented and discussed. The high prevalence of digital usage and strong correlations between sleep issues and digital activity indices in Chinese working youth highlighted the necessity to perform this study.

Next, we divided sleep duration into three categories: short (<7 h), normal (7–9h), and long (>9 h) according to previous literature and the recommended standards from health departments and conducted multilevel ordinal logistic regression analyses between it and digital activity to test whether the association existed. If it did exist, what exactly were the interactions between various measurements? We reported a non-significant correlation between most digital activity measures and sleep duration for average, workday, and free day. To some extent, this result seems to support the time shifting hypothesis which reported that digital activities coincided with sleep schedule, delayed the time both going to sleep and rise-up.[23,26–28] However, this hypothesis was proven by most research conducted among college students who had a flexible time schedule, and thus would not be applicable to working youth who had a\ strict work schedules. This observation was novel and surprising, however explicable. A possible explanation is that our sample, on average, received the recommended amount of sleep (see Table 1, 7.60–8.40 h per night), which was not significant. Moreover, this result may indicate that working youth who did not access the Internet had a habit of sleeping and rising early, while those ones who engaged in digital activities were more likely to sleep late and intentionally rise as late as possible to ensure they have energy during the day. Although the correlation between the former two was not significant, we still found that Chinese working youth who engaged in digital activities would sleep less on workdays and more on free days, which was similar to the previous literature.[54,55] This could be explained by two possible reasons. First, youth sleep is more closely influenced by their work schedules on workdays or weekdays; thus, they must shorten their sleep duration to wake up on time the next day, although they did not sleep during the preceding night. Second, self-regulation resource theory points out that longtime vigilance could drain an individual's energy, therefore they need a longer rest time to revive, such as sufficient sleep.[56] They often tend to recover and compensate for less sleep by lengthening their sleep duration on free days, when there is no mandatory wake-up time.

In contrast, several significant associations were observed in this study. Unsimilar to the correlation with sleep duration, all digital activity measures positively predicted bedtimes. Specifically, those who surfed the Internet more frequently and for a longer time went to bed much later than those with lower frequency and shorter digital activity duration, which is supported by most current studies.[23,27,33,41] Although some researchers elucidated the phenomenon by increased physiological and emotional arousal, blue-light exposure, and time displacement,[30] these theoretical options were focused on media use before going to bed or pre-sleep, which may not explain our results. Nevertheless, self-regulation resource theory provided us with a scalable understanding of the effect of digital usage during other time periods, except late night. This theory indicated that the self-regulation resources possessed were limited and that they may encounter ego-depletion once their resources are consumed excessively. As highly frequent or uncontrolled digital device use may consume a lot of time and energy during the day, it seems logical to assume that sleep procrastination can be explained by this theory.[57,58] Furthermore, we tested the impacts of five digital activities on bedtime and found that the impacts of digital socialization and shopping on bedtime may be slightly bigger than the other three activities, which was consistent with the large chunks of existing studies relevant to social media.[35,36,43] Currently, digital social media is developed as a strong affordable, multifunctional aggregation platform beyond the sole social nature, and can meet various needs including learning and working. The effect of digital shopping on bedtime onset was attributed to its high prevalence and time distribution which was concentrated in 11:00–12:00 and 19:00–24:00 time slots.[3] Additionally, live-streaming e-commerce is one of the most common online shopping methods for young people due to the dual nature of both telepresence and interaction. An increasing number of young people are squatting in anchors' studios to buy things they want, look on, and/or engage in interaction with the anchors or other buyers after work at night, which may delay their sleeping time. Despite differences in the impacts of various digital activities, their frequency both during the day and at bedtime was predictive of later bedtime.

For a society characterized by chronically late and short sleep, individuals are concerned about sleep quality, which is a global subjective perception of sleep status. We also examined the association between digital activity and sleep quality. In addition to global frequency, sleep quality was significantly associated with the frequency of each type of digital activity, including online working, learning, socialization, entertainment, and shopping. Since the definition and measurement standards of digital activity frequency in our study were obscure and subjective, we could not identify the optimal frequency contributing to good sleep quality. Apart from a negative correlation between digital activities and sleep quality which supports existing literature,[26,44,59–61] the most creative and valuable result was that we also explored the complex nature of their association. We found a dose-response relationship pattern between digital activity duration and sleep quality and identified the appropriate duration range (22.5–27.5 hours per week) that contributed to optimal sleep quality. The sleep-related outcomes of digital activity vary depending on users' intentions,[23,27,62] active vs passive,[44] daytime vs pre-sleep,[30] and media types.[29] For instance, Exelmans and Van den Bulck (2014) tested the impact of books, television, music, Internet, and video games on sleep issues in young adults, and found that although these media use impaired sleep quality, they still used them as a sleep aid to consume pre-sleep time, alleviate negative emotions, and stress.[27]

Finally, age is a determining factor in sleep behavior and is related to digital use. Related research suggests that the relationship between sleep and digital media use is different in various age groups.[22,23] Hence, we analyzed the moderating role of age and found significant interactions between digital activity frequency, duration, and age for sleep duration and bedtime rather than sleep quality. Regarding sleep duration, although digital activity frequency and duration did not predict sleep duration for all working youth, their relationship was moderated by age. Moreover, age significantly moderated the association between duration of digital activity and bedtime. In other words, younger youths who spent more time on digital activity tended to go to sleep significantly later and had a short sleep duration than older youths. A possible explanation for this warrants further investigation: older youths tend to have higher life or work stress that causes them to sacrifice their own time to do housework, cooking, or take care of children and parents before or after work. This may result in a tendency to compensate for lost time by compressing sleep duration. In addition, age-related factors may influence sleep behaviors, and individuals tend to sleep less with age due to the reduced secretion of melatonin, especially after 35 years of age.[63] Contrary to what we expected, the relationships between digital activity frequency, duration, bedtime, and sleep quality were not moderated by age. The results suggested that different processes between digital use and sleep might occur in different age groups, yielding differing results.[23] The studies regarding Chinese population reported that the chronotype composition of the young population changed slightly between the 18- and 49-years groups,[64] and there was no correlation between age and chronotype among the Chinese youth aged 18–49 years.[65] One possible explanation was that this population were concurrently working with the similar work schedule demands. The relationship patterns between digital frequency, duration, and sleep quality were similar regardless of age for all Chinese working youth, therefore more frequent and longer digital activity would impair sleep quality.

The concern about technology impairing sleep status has increased in academic literature. The current study focused on working youth who are vulnerable and sensitive to sleep problems, however lack attention from the public and scholars. The strengths of the current study lie in the large, representative sample of Chinese working youth based on the CFPS, as well as the identification of the appropriate digital activity duration range for optimal sleep quality. Despite the robust results of our study, there are several limitations. First, measurement error or even self-report bias may creep in due to the use of self-administered questionnaires. Therefore, novel tools or methods to obtain data should be developed, such as smartwatches and other wearable devices, to investigate their correlation and mechanism. Second, although we tested the potential effect of different digital activities, the time allocation of each activity was missing in our data, therefore the effect size of each activity could not be computed, which should be further explored in future work. It is also possible that unmeasured variables, such as fear of missing out, self-control ability, bedmates/roommates, family relation may account for the association or mechanism between them. Additionally, cross-sectional data analysis could not establish the causation or direction of the effect. Future studies should include longitudinal data or experimental designs to support both causation and direction of effects.

## Conclusion

In summary, this study demonstrated that digital activity in daily life could predict later bedtime and poor sleep quality; however it was not associated with sleep quality. Furthermore, it revealed that the overall number, frequency, and duration of digital activities was significantly correlated with both bedtime and sleep quality. In other words, those working youth who engaged in digital activities more frequently and longer would sleep later and have poorer sleep quality than those who did not, or did so just occasionally. Although global digital activity duration negatively predicted sleep quality, appropriate digital activity duration (less than 25 hours per week) seemed to prompt Chinese working youth sleep quality. Therefore, blindly preventing or simply reducing the amount of digital activity before going to sleep will not prevent or mitigate the potentially negative effects on sleep.

## Institutional Review Board Statement

CFPS, an ongoing project launched by the Institute of Social Science Survey at Peking University was approved by PU IRS and the project ethics review batch number was IRB00001052-14010.

## Data Sharing Statement

The CFPS data was obtained online http://www.isss.pku.edu.cn/cfps/en/data/public/index.htm (accessed on 15 January 2021), which is available to users worldwide (registration and approval needed).

## Informed Consent Statement

The China Social Survey Center informed all respondents of relevant matters before conducting the survey in accordance with the requirements of the research ethics review of China. All respondents in the CFPS survey signed an informed consent form (http://www.isss.pku.edu.cn/cfps/docs/20201019094434868765.jpg?CSRFT=X1JX-TOEW-914M-QK8F-M5GA-1F8Z-3EUI-OYRW accessed on 15th Nov. 2021) before the interview. The participants' personal privacy information in all public data was deleted, and researchers can directly apply online to obtain the data without ethical review.

## Acknowledgments

This study is based on publicly available data from CFPS, which was a huge project that required immense effort from many individuals. We would like to thank the CFPS research team members, field survey participants and respondents.

## Funding

Major Program of National Fund of Philosophy and Social Science of China: 18VZL009.

## Disclosure

The authors declare no conflicts of interest for this work.

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