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**Article**

# Measuring SNS Use with iPhone "Screen Time" Among a Sample of Chinese College Students: Applying Application-Tracked Data in Communication Research

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**Abstract**

In the last twenty years, many studies have focused on the relationship between social networking site (SNS) use and people's subjective well-being. However, obtaining accurate information on users' activities on SNS remains a problem. This study applies the "Screen Time" function on the smartphone to record the young generation's online activities in the Chinese context. This survey was conducted in June 2019. Among a sample of 100 Chinese college students who used SNS on a regular basis and managed to upload a screenshot of the "Screen Time" report at the end of the day, it was confirmed that the discrepancy between self-reported usage and application-traced data was statistically significant. The self-report measure positively correlated, but only moderately, with the "Screen Time" data, $r = .588$, $p < .01$. Especially when respondents had spent over three hours on SNS in one day, they were more likely to underreport their usage. No significant correlation was found between time spent on SNS and subjective well-being. However, there was a moderate positive correlation between the intensity of SNS use and fear of missing-out, $r = .215$, $p < .05$.

This study again draws attention to the point that the quantitative SNS usage per se is not enough to reach conclusions concerning well-being outcomes. In future studies regarding the use of new technologies and people's psychological health, it is worth addressing how the content and mode of social media use would affect well-being.

**Key words:** Screen Time, SNS, measures, digital technology, subjective well-being, health communication

## Introduction

Since the advent of social networking sites (SNS), they have rapidly become popular worldwide, and markedly changed the way people live, work, and socialize. According to a recent market report by Statista (Clement, 2019), the number of active social media users had reached 3.73 billion by October 2019. In the same year, the global social media penetration rate had reached 45 percent, with East Asia and North America sharing the highest penetration rate at 70 percent.

China is the world's largest social media market. According to a research report by Statista (Thomala, 2020), the number of social network users in China had reached 708.4 million in 2019. In the same year, the penetration rate of social media in China had reached 72%. Among the most popular Chinese social networks (i.e., WeChat, Tik Tok, QQ, and Sina Weibo), WeChat enjoys the highest popularity: the number of active users was about 1,165 million by April 2020. Additionally, according to Statista (Thomala, 2020), almost fifteen percent of the mobile screen time was spent on instant messaging apps, like WeChat and QQ.

Given that people are spending more and more time on screens, many attempts have been made to explore the relationship between SNS use and users' psychological status over the last two decades, especially to understand the nature of people's various experiences on social media and the mechanisms that may disrupt well-being. For example, Chen et al. (2016) conducted a study on social network site use and subjective well-being, in which they found that passive SNS use was negatively associated with subjective well-being, and self-esteem mediated the effect of passive SNS use on well-being. Shakya and Christakis' (2017) longitudinal study assessing the associations between SNS use and physical and psychological health suggested that using Facebook was negatively associated with well-being. Weinstein's (2018) study also contributed to prior research by exploring how social networking sites' daily interactions influence adolescents' affective well-being.

Although many scholars have been trying to quantify users' online social interactions, how to obtain accurate records of their social media behaviour remains a significant challenge for new media studies. Self-reporting is among the most widely used measures in data collection because of its convenience and high accessibility. However, it is also among the most criticized for its response bias, resulting in misreporting, which may easily affect data accuracy. Previous studies have shown that compared with log file data, the accuracy of self-reports of internet use or other mobile phone behaviour is relatively low and only moderately correlated with objective data (Boase & Ling, 2013; Scharkow, 2016). Therefore, it is necessary to apply a new approach to collect more accurate data.

The present paper builds on these established findings by addressing the role of “Screen Time,” a function on the smartphone which is designed to provide users with information on how much time is spent on apps and websites, as a potentially valid measurement of social media behaviour and examining the correlation between self-reporting measure and application-traced data. Additionally, this paper will further discuss the relationship between time spent on SNS and users' subjective well-being in a sample of Chinese college students.

## 1. Literature Review

### 1.1 Social Networking Sites

There has been a consensus within the academy that any internet-based applications that allow the creation and exchange of user-generated content (UGC) can be considered as “social media” (Kaplan & Haenlein, 2010). In addition to the most used, that is, Facebook and Twitter, online video-sharing sites exemplified by YouTube are also regarded as social media because registered users can express their likes or dislikes on the videos and leave comments in the community (Khan, 2017). Online virtual games can be categorized as social media in some contexts as long as players have the facility to build online communities, chat, and make internet phone calls. Even online shopping sites exhibit some social media functions, considering customers are encouraged to post reviews on product pages. On the other hand, social networking sites are more focused on users' online interactions by enabling users to create a public or semi-public profile and interact with each other in their networks (Subrahmanyam, Reich, Waechter, & Espinoza, 2008).

New social networking platforms are springing up, each with its own functional characteristics. Based on previous studies, instead of coming up with a one-size-fits-all definition, SNS, as defined in this study, should at least meet the following two basic requirements: allow self-presentation and have a certain level of media richness (Kaplan & Haenlein, 2010). Information richness refers to “the ability of information to change understanding within a time interval” (Daft & Lengel, 1986). Rich media provides the capacity to process complex and subjective messages, like Instagram and Twitter, while media of low richness process fewer cues and restrict feedback, like instant messaging services. Given that this study mainly discusses text- and picture-based communication, video sharing platforms are not included. In total, 12 platforms were selected in this study. In addition to Facebook, Twitter, Instagram, LINE, and WhatsApp, this research also selected the six most used social networking sites in mainland China, including WeChat[1], Sina Weibo[2], and QQ[3]. Forum-based online communities that allow users to create personal profiles, post original content, and directly exchange e-mails or instant messages with other users are also included in this study, including Douban[4], Zhihu[5] and Baidu Tieba[6]. All of these above-mentioned applications are classified as social networking in the "Screen Time" function.

### 1.2 SNS use and subjective well-being

Previous studies about the influence of SNS on well-being have yielded mixed results. Some researchers suggest that social media use has positive effects on the user's psychological well-being. For example, a recent study by Kim and Kim (2017) found that online interaction was positively related to people's network heterogeneity, which would enhance both bonding and bridging social capital and lead to improved subjective well-being. Similarly, Forbush & Foucault-Welles' (2016) study of the correlation between SNS use and the adaptation of college students studying abroad proved that those who used SNSs more often during their study abroad preparation had more extensive and more diverse social networks abroad, which predicted significantly higher levels of social and academic adaptation in the host culture.

Also, since the use of social media and people's online behaviour is firmly embedded within a political, social, and cultural context, there has been an increasing amount of literature focusing on social media use and well-being in the Chinese context. Pang's (2018) study on time spent on WeChat and the subjective well-being of college students showed that WeChat use time exerted a positive effect on social integration, bonding relationships, and bridging relationships, which may improve their sense of subjective well-being. This finding is consistent with Chan's (2015) research examining mobile social media's role in moderating psychological well-being, which showed that communicative use and self-disclosure on mobile social media were positively related to bonding and bridging social capital and well-being.

Other scholars argue that problematic social media use may be negatively related to life satisfaction and degrade well-being. Satici and Uysal's (2015) study demonstrated that excessive use of Facebook might decrease the user's subjective vitality and subjective happiness. Brooks' (2015) work has also shown that overexposure to social media negatively affected people's working performance, leading to low working efficiency and poor subjective happiness. In the same vein, (Brooks, 2015; Du, van Koningsbruggen, & Kerkhof, 2018) again confirmed that overuse of social media was positively associated with the absence of self-control, resulting in poor task performance and generating the sense of guilt, which undermined people's sense of accomplishment. Another mechanism that may disrupt subjective well-being is online social comparison generating dispositional envy: users tend to present their best sides on social media, so that, when over-exposed to other people's highlight reels, the upward comparison fuels debilitating envy, which directly leads to negative emotional feelings (Lin, R. & Utz, 2015; Steers, Wickham, & Acitelli, 2014; Tandoc Jr, Ferrucci, & Duffy, 2015; Vogel, Rose, Roberts, & Eckles, 2014).

There are a few possible explanations about these mixed findings: first and foremost, the relationship between social media usage and well-being is not an either-or scheme; in fact, both positive and negative effects co-exist at the same time on opposite sides of a see-saw. The see-saw maintains a dynamic balance and is weighted by positive and negative influence (Weinstein, 2018). Apparently, subjective well-being is mediated by various factors. For instance, bridging and bonding social capital have been proved to be positively associated with subjective well-being. A large amount of literature has shown that intimate relationships, or strong ties, with family members or close friends provide bonding social capital, while weak ties that travel in different circles generate bridging social capital (Burke, Kraut, & Marlow, 2011; Wellman & Wortley, 1990). Accordingly, SNS activities that help form and maintain social capital might boost well-being (Ellison, Nicole B., Steinfield, & Lampe, 2007; Yip et al., 2007). Yet studies that explicitly examine anxiety and depression tell a different story: Woods and Scott's (2016) study found that people who used social media more and who were more emotionally invested in social media experienced poorer sleep quality, lower self-esteem and higher levels of anxiety and depression. A qualitative focus group discussion conducted by O'Reilly et al. (2018) among fifty-four adolescents also showed that those young people perceived social media as a threat to mental well-being because it was believed to cause mood and anxiety disorders for some people, and sometimes it was even viewed as a platform for cyber-bullying. Given that several factors jointly influence subjective well-being, studies applied different factors that always yield different results.

Another possible explanation for the inconsistent findings is that these studies measured social media usage in different ways. Some scholars focused on various functions of social media use and categorized the usage as, for instance, communicative and non-communicative or information-seeking and time-passing activities (Burke et al., 2011; Chan, 2015), while other researchers put more emphasis on the time spent on social media and the frequency of social media use (Tandoc Jr et al., 2015; Valkenburg, Peter, & Schouten, 2006; Valkenburg & Peter, 2007). Although each of the above-mentioned social media measures has its own merits, it is necessary to apply a more comprehensive measure that provides an all-inclusive information about detailed SNS activities and usage intensities.

"Screen Time" seems to be a possible solution to this problem. Since over-exposure to mobile devices has become a social issue, smartphone developers have been paying increasing attention to users' well-being in recent years. In 2018, the iOS system by Apple Inc. launched a new function called "Screen Time" which allows its users to know how much time they have spent on apps and websites on their devices every day. To the best of the author's knowledge, there is still a shortage of empirical research utilizing "Screen Time" as an indicator of social media usage intensity. This study investigates this function on the smartphone and compares self-report measures of SNS use with application-traced data, to evaluate the criterion validity of the self-reporting approach. Furthermore, this study plans to examine the association of "Screen Time" with subjective well-being to shed light on whether time spent on SNS can be used as a predictor of subjective well-being.

### 1.3 Self-reporting SNS use and the iPhone "Screen Time"

As mentioned before, previous studies on the effect of mobile phone and social media use rely heavily on participants' self-reporting of their phone activities. However, the self-reporting approach has long been criticized as lacking accuracy. Boase and Ling's (2013) study comparing self-report mobile phone use with server log data found that the correlations between self-report measures and log data were moderate, questioning the validity of self-report data. In the same vein, Abeele et al. (2013) conducted another study comparing self-reported and actual usage of mobile phones among 466 adults in Belgium, which also found significant discrepancies between self-reported and objective usage. Scharkow's (2016) work comparing self-reports of Internet use with client log files from more than three thousand household samples again confirmed that the accuracy of self-reported frequency and Internet use duration was unsatisfactory.

The recall bias of social media and mobile phone use has been a major concern in this field: from the participant's perspective, people typically find it difficult to recall accurately the time they have spent on social media activities. Schwarz and Oyserman (2001) put forward three possible reasons that may lead to recall failure: first, memory decreases over time; second, respondents find it hard to have detailed representations of numerous individual episodes of frequently repeated behaviour; and third, since our autobiographical knowledge is stored in a hierarchical network in order of importance, retrieval of past events that are represented at a low level of hierarchy may be difficult. In this case, given that using social media is a trivial, fragmented, and frequently repeated activity, recall failure seems inevitable.

Some scholars managed to repeat questionnaire surveys several times in order to have a better record of participants' online activities. For example, in a study of Facebook use and subjective well-being of young adults, Kross and his colleagues (2013) randomly text-messaged participants five times per day between 10 am and midnight and asked them to report how much had they had used Facebook since the last time they were asked. Such manipulation, to some extent, helps to reduce the recall bias. Nevertheless, given that the response options of social media use intensity are dominantly Likert scale (ranged from 1 *seldom* to 5 *several times a day*, etc.) or multiple choice (0 to 30 minutes, 31 minutes to 60 minutes, etc.), it is still very hard to obtain accurate data of usage outside the laboratory.

Recently, the "Screen Time" function on the iOS systems has received great research attention (e.g., Sewall, Bear, Merranko, & Rosen, 2020). "Screen Time" not only records the accurate time that people spend on the mobile phones, but it also provides people with the following information: 1) the most used application in the past day; 2) the amount of time people spend for different purposes (e.g., social networking, productive, reading and reference, etc.); 3) the number of mobile phone pick-ups and the first used application after pick-up; and 4) numbers of notifications. "Screen Time" data is available for one calendar day. A weekly report is also available at the end of the week, which records daily average screen time and most-used apps in the past week. A similar function is available on the Android system as well: Android users can download the applications called "Digital Wellbeing" or "Digitox" from the Google store. However, I decided to only apply the iPhone "Screen Time" for the following three reasons. First, when recruiting research participants in 2019, the "Screen Time" feature was installed with the iOS by default, whilst most Android users needed to manually download and install such usage-tracking applications. Therefore, there is a better chance to recruit iPhone users with their "Screen Time" function turned on than to recruit Android users who happened to have installed "Digital Wellbeing" or "Digitox". Second, in 2019 when this study was conducted, the information provided by "Digital Wellbeing" and "Digitox" is slightly different from the "Screen Time" report. For example, "Digital Wellbeing" only tells users the time they have spent on each application (i.e., Calendar, YouTube, Chrome, etc.) and does not report overall time spent for different purposes (i.e., productivity, social networking, etc.). Therefore, it was harder to get an overall picture regarding users' digital behaviour. Third, due to Internet blocking, the Google Play app store is not available in mainland China. Hence, for those potential participants who resided in mainland China, it might be difficult to get access to these applications. For these reasons, I decided to only focus on iPhone users in this study.

As mentioned above, several lines of evidence suggest that the intensity of social media use and subjective well-being appear to be closely linked (Tandoc Jr et al., 2015; Valenzuela, Park, & Kee, 2009; Vogel et al., 2014; Weinstein, 2018). Given that previous studies were mainly built upon self-report social media behaviour, there is an urgent need to improve social media activity accuracy as a valid variable. Hence, this study aims to answer the following research questions:

**RQ1**: How well does the self-reporting measure compare to "Screen Time" data?

**RQ2**: In which situations are people more likely to over- or under-report SNS use? What are the demographic characteristics associated with over- and under-reporting of SNS use?

**RQ3**: How is time spent on SNS related to young adults' subjective well-being?

## 2. Research Design

### 2.1 Procedures

This study was conducted in June 2019. The data presented in this paper were collected in an online survey over the course of one month. All of the qualified participants were asked to complete the questionnaire regarding their daily use of SNS and subjective well-being at the end of the day before bedtime. At the end of the questionnaire survey, participants were encouraged to write down their comments and advice concerning the survey. Also, participants were asked if they were interested in a further one-to-one study regarding social media use and well-being.

### 2.2 Participants

Potential participants had to meet the following requirements: 1) College students currently enrolled in undergraduate or graduate programs; 2) Mandarin speakers; 3) Those use an iPhone with iOS Version 12 or later and "Screen Time" function turned on; 4) Users of social networking sites on a regular basis; 5) Those able to finish the questionnaire at the end of the day and upload a screenshot of "Screen Time" for that day. All of the participants were notified in advance that the study would be about time spent on SNS and well-being. They could stop the survey and be free to withdraw from the project at any time they wished. Participants were asked to finish the questionnaire on a day of their convenience, and no repeat was required.

This study applied a convenience sampling method. The survey was distributed among 375 Chinese college students; however, since screenshots of the "Screen Time" report may contain some personal information, the response rate was less than 30%. Overall, a hundred college students who used SNS on a regular basis managed to finish the online questionnaire and upload a valid screenshot at the end of the day. The demographic composition of those sharing their "Screen Time" information is as follows: sixty-nine are female (69%); forty-seven are undergraduate students (47%), fifty-three are postgraduate masters students (53%) with eighteen people enrolled in doctoral programs (18%); and fifty-four are currently studying outside mainland China (54%). Regarding age distribution, 14% of the participants ranged between seventeen and nineteen years of age, 34% of them were aged between twenty and twenty-two years, 29% ranged between twenty-three and twenty-five years of age, and 23% were over twenty-six years of age.

### 2.3 Measures

#### 2.3.1 Self-Report Measures

Before uploading a screenshot of "Screen Time" in the questionnaire survey, participants were asked, "How many hours do you think you spent on social networking sites today? *No longer than 0.5 hours, 0.5-1 hours, 1-1.5 hours, 1.5-2 hours, 2-2.5 hours, 2.5-3 hours, More than 3 hours.*" This question was designed to measure the self-reported intensity of social media use. After uploading a screenshot of the time-tracking app, they were asked whether the actual time spent on SNS was longer or shorter than their assumptions.

#### 2.3.2 "Screen Time" Data

"Screen Time" data includes overall time spent on a mobile phone on a calendar day, time spent on each category (i.e., social networking, productive, entertainment, other), most used applications, time spent on each app, pick-ups, and the number of notifications. This study only counted the overall screen time, time spent on social networking, and time spent on most-used apps. The "Screen Time" data was used for comparison with the self-report measures of social media daily use. An example of a "Screen Time" screenshot is presented below (Figure 1). According to the instruction, participants were expected to upload a screenshot, as shown in Figure 1 (right), which contains information on the total

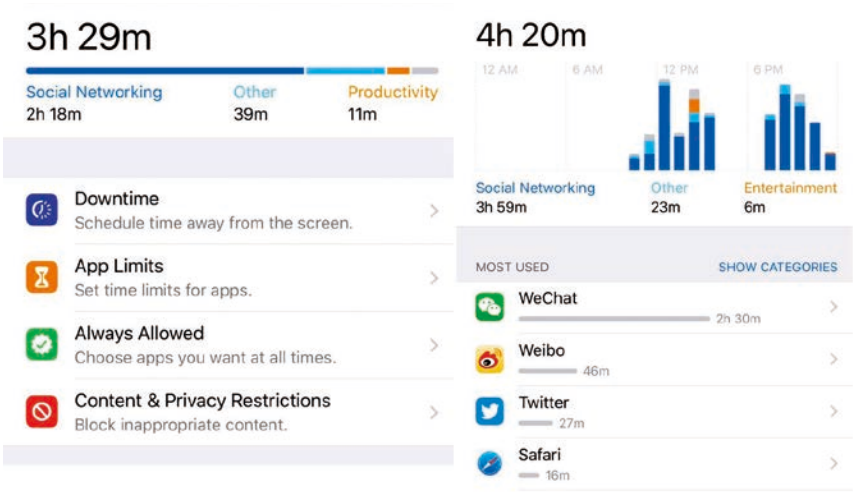


**Figure 1.** *Left*, a brief view of "Screen Time"; *Right*, detailed information of the screenshot of "Screen Time".

time spent on mobile phones on that day, time spent on each category, and most used applications. However, some of the participants only uploaded a brief view screenshot, as shown in Figure 1 (left), which did not give detailed social media information. Given that such pictures at least tell the overall time spent on social networking, those participants who uploaded the brief-view-style photo were also counted as valid. However, they would not be included in further discussions regarding particular social media behaviour. To enable comparison with self-reported data, Screen Time report of the actual time spent on SNS was also coded into seven categories, respectively, from *no more than 0.5 hours to more than 3 hours.*

#### 2.3.3 Social connectedness

Social connectedness was measured from three perspectives: fear of missing out (FoMO), bridging social capital, and bonding social capital.

Fear of missing out (FoMO) is a kind of social anxiety characterized by "a desire to stay continually connected with what others are doing" (Przybylski, Murayama, DeHaan, & Gladwell, 2013). Fear of missing out was examined via four items, including "I get anxious when I don't know what my friends and family are up to" and "I get worried when I don't know what is going on in the society", etc. A reliability analysis was carried out and the Cronbach's alpha showed the scales to reach acceptable reliability ($\alpha = 0.76$). Bridging social capital (Cronbach's $\alpha = 0.76$) and bonding social capital (Cronbach's $\alpha = 0.77$) scales were adapted from the study regarding the benefits of Facebook "Friends" on social capital (Ellison, Nicole, Steinfield, & Lampe, 2006). The internal consistency of both these two scales was satisfactory. Response options ranged from 1 (*strongly disagree*) to 5 (*strongly agree*).

#### 2.3.4 Subjective Well-Being

This study applied the satisfaction with life scale developed by Diener et al. (1985). To make the statements more specific, the scale was divided into two parts: school life and social life. Each part consisted of five items, for example, "I am satisfied with my school life" and "In most ways my social life is close to my ideal." Response options ranged from 1 (*strongly disagree*) to 5 (*strongly agree*). Both of these two scales had excellent reliability ($\alpha$ (social) = 0.81, $\alpha$ (school) = 0.91).

## 3. Results

This study applied an exploratory analysis approach. To address the first research question, it was necessary to compare the "Screen Time" data with the self-report measures using Spearman's correlation test. The result showed that there was a moderate correlation between self-report SNS use and "Screen Time" data, which was statistically significant ($r_s = .588$, $p < .01$).

Next, I compared the self-report measures directly to the "Screen Time" data to understand exactly how the self-report SNS use differs from the application-traced data. Overall, 15% of the participants over-reported their usage, 47% under-reported, and the rest 38% of all the respondents had a relatively accurate estimation of time they had spent on SNS that day.

The percentage of participants in each category of both self-report SNS use and "Screen Time" measurement is presented below (Table 1). Typically, there was a higher percentage of participants in each category of the self-report measures than in each category of the "Screen Time" measures, with the significant exception that participants who actually had spent a relatively long time on SNS did not report this extended usage in the self-report measures. The "Screen Time" data showed that 53% of the participants spent more than three hours on social networking in one day; however, only 33% of them self-reported having this high level of SNS usage. This finding indicates that participants were reluctant to admit that they had actually spent so much time on social networking sites in one day.

**Table 1.** Percent comparison of the self-report SNS use and Screen Time data (N=100)

| | Self-report | Screen Time | Difference |
|---|---|---|---|
| **No more than 0.5 hours** | 2 | 2 | 0 |
| **0.5 – 1 hour** | 8 | 4 | 4 |
| **1 – 1.5 hours** | 23 | 8 | 15 |
| **1.5 – 2 hours** | 13 | 13 | 0 |
| **2 – 2.5 hours** | 12 | 12 | 0 |
| **2.5 – 3 hours** | 9 | 8 | 1 |
| **More than 3 hours** | 33 | 53 | -20 |
| **Total percent** | 100 | 100 | |

A chi-square goodness-of-fit test was also conducted to verify if the discrepancy between self-report usage and application-traced data was statistically significant. This test enables us to compare respondents' frequency in each category of the self-report measures with the frequencies that should be expected based on the objectively recorded data. The test result showed that there was a statistically significant difference between the frequencies of respondents in the categories of the self-report measure and the frequencies that could be expected based on the "Screen Time" measure, chisq (6) = 43.244, $p < .01$.

To sum up, regarding the first research question, it has been shown that although the self-report measure of daily SNS use was moderately correlated with the "Screen Time" measure, generally, it did not compare favourably to the actual usage. Especially when respondents had spent a relatively long time (over three hours, for example) on SNS in that day, they were more likely to under-report their social media usage.

There are three possible explanations of this phenomenon. First and foremost, a previous study has shown that extended exposure to social media may generate feelings of guilt due to low self-efficacy and negative self-appraisal (Lin, L. Y. et al., 2016). Under-reporting SNS's use seems like a psychological comforter that frees people from rumination and eases the sense of guilt. The second explanation is that the fragmentation of social media use makes people lose track of time. On the one hand, people may simply underestimate the frequency of using SNS. As mentioned before, a large body of research has proved that people tend to underestimate the frequency of mundane, frequently occurring behaviour (Schwarz & Oyserman, 2001; Sudman, Bradburn, & Schwarz, 1997). Overuse of social media may blunt people's feelings and make it difficult to precisely recall the time they have spent on social media.

On the other hand, the fragmented use of SNS also renders vagueness in the recall, given that there is an increasing number of social networking platforms. However, it may be that people are not spending too much time on one specific platform; the accumulative time spent on social networking sites together eventually goes far beyond the individual's expectation. Last but not least, entertainment and leisure activities may also lead to underestimation of time spent on SNS. According to the questionnaire survey, one of SNS's main purposes is entertaining and sharing interest: 57% of the respondents said they use SNS for pleasure. When people use SNS for fun, they are more likely to be unaware of how much time they have been devoting to their devices.

To address the second research question and find out if any demographic characteristics were correlated with misreporting of SNS use, a logistic regression analysis was also conducted. Respondents who selected a self-report category that differed from the appropriate category indicated by the "Screen Time" data were coded as "under-reporting" or "over-reporting" accordingly. The results of this analysis are showed in Table 2.

According to the analysis results, it can be seen that none of these demographic factors (gender, age, or educational background) was significantly associated with under- or over-reporting of SNS use. Namely, this analysis indicates that demographic traits did not explain the under- and over-reporting variance that occurs with the self-report measure.

Boase and Ling (2013) conducted a study in Norway comparing self-report mobile phone use with server log data and found that males were more likely to over-report their mobile phone use when being asked "how often do you use a mobile phone to call

**Table 2.** Logistic regression analysis of over-reporting and under-reporting of self-report measures

| | DV=self-reporting bias | | | |
|---|---|---|---|---|
| | Beta | s.e. | d.f. | p |
| **Gender** | .387 | .650 | 1 | .551 |
| **Age** | .178 | .535 | 1 | .110 |
| **Education** | -.645 | .664 | 1 | .332 |
| **$R^2$** | .029 | | | |
| **Adjusted $R^2$** | .043 | | | |
| **N** | 62 | | | |

others or to send/receive text messages per day?" This is in conflict with the findings in this study, and I can suggest one possible explanation for the inconsistency. Participants from Boase and Ling's study were nationally representative and came from all age groups. In that study, both private and business phone calls were included in data collection. Given that business phone calls may give the impression of lasting longer and happening more often, people who were employed and had to have business phone calls were more likely to over-report their mobile phone use. According to data from the European Statistical Office, in 2008, the employment rate in Norway was 84.8% for males and 78.6% for females (Eurostat, 2020). Since the gender ratio in Boase and Ling's study was well-balanced, and 50% of the participants were female, it can be inferred that male respondents in that study were more likely to be employed than female respondents. Therefore, their study found that males were more likely to over-report their mobile phone use. However, in my study, all of the respondents were full-time students, and their use of mobile phones was mainly for entertainment, private communication, and information acquisition. In that vein, it makes sense that demographic traits are not related to the self-report bias.

In sum, this exploratory analysis suggests that "Screen Time" is a more reliable measure of daily SNS activities than the traditional self-report measure. Given that existing literature mainly applied a self-report measure in discussing the relationship between social media use and subjective well-being, this study brings the reliability of self-report data into question. Therefore, this study would like to test further the correlation between time spent on social networking sites and people's subjective well-being based on data collected from "Screen Time".

There were significant individual differences in the time spent on the mobile phone and SNS. Among the one hundred participants, the maximum time spent on SNS reached 665 minutes in one day, while the minimum was only 15 minutes (M=204.26, SD=121.05). "Screen Time" data showed that WeChat was the most used social networking application for 57.6% of the eighty-five valid respondents. Weibo took second place: 20% of the respondents used more Weibo than other SNS in one day.

Before the correlation analysis of time spent on SNS and subjective well-being, I first examined the relationships between SNS time and social connectedness. There was a moderate positive correlation between the intensity of SNS use and fear of missing-out ($r = .215$, $p < .05$), which indicated that the more time someone spent on SNS, the more likely he or she would experience the fear of missing-out.

Then a zero-order correlation analysis was conducted to explore the intertwined relationships among the main research variables. The results are presented in Table 3.

**Table 3.** Descriptive and nonparametric correlations among the key variables

| Variables | M | SD | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|---|
| **1. SNS time (min)** | 204.26 | 121.05 | 1.00 | | | |
| **2. SWB (social)** | 16.42 | 3.82 | .18 | 1.00 | | |
| **3. SWB (school)** | 15.21 | 4.61 | -.05 | .57** | 1.00 | |
| **4. Happiness** | 13.67 | 2.27 | .00 | .38** | .03** | 1.00 |

Notes: N=100. *$p < .05$; **$p < .01$

No significant correlation was found between time spent on SNS and subjective well-being, which is at odds with existing studies that have verified that using SNS appears to exert impacts on psychological well-being. A possible explanation can be speculated. Instead of discussing the intensity of using one specific social media, the "Screen Time" report blends all SNS platforms into one global picture. In that sense, activities like chatting online using WeChat and LINE, browsing information via Twitter and Facebook, posting on Instagram and Weibo, are all counted in the "Screen Time" report. Previous studies have shown that using social media for a different purpose may exert different impacts on well-being. For example, communicating with others on SNS may enhance users' well-being by positively influencing bonding and bridging social capital (Kim & Kim, 2017), while passively browsing others' posts and engaging in online comparisons may exert adverse effects (Steers et al., 2014). Yet obviously, in the real world, people's online activities are diversified, and the survey results also show that all of these participants are using more than one social media platform. It seems impossible that these activities happen separately in one day. Therefore, when all these activities happen simultaneously, as Weinstein's (2017) research showed, the relationship between social media usage and psychological well-being – whether enhanced or decreased – is no longer confined to an 'either/or' framework. Instead, both positive and negative influences co-exist, lying on the opposite sides of the emotional see-saw of well-being. Consequently, when testing the relationship between the intensity of the overall use of SNS and well-being, the association becomes non-distinctive.

## 4. Discussion

This study was designed to answer three questions: first, how well does the self-report measure compare to "Screen Time" data; second, if there are discrepancies between self-report social media use and "Screen Time" data, in which situation are people more likely to misreport the usage, and what are the demographic characteristics associated with over- and underreporting of SNS use; last but not least, if "Screen Time" is a more reliable measure of daily social media behaviour, is there any association between time spent on social media and people's subjective well-being. Using survey data and "Screen Time" reports collected from Chinese college students, the following findings can be reported.

First, although self-reporting daily social media use measures are not fully out of line with actual behaviour recorded by "Screen Time", this study shows that there is still a statistically significant discrepancy between the self-report data and the "Screen Time" report. This result agrees with previous studies comparing self-reported and observed mobile phone use (Boase & Ling, 2013; Vanden Abeele et al., 2013), which also found significant discrepancies between self-reported and log data.

Second, users who spend more than three hours on SNS in one day are particularly prone to under-report their usage. In addition to limited recall ability, Schwarz and Oyserman (2001) found other reasons for underestimation, including social desirability and self-satisfaction. They suggested that respondents may deliberately "edit" their responses when providing answers to the interviewer if they consider they "did not engage in the desired behaviour or did engage in the undesirable one", resulting in over- or under-reporting. In this case, the overuse of social media appears to be an unwished-for behaviour because it is always associated with low self-control, lack of self-discipline, over-reliance on technology, and the inability to delay gratification. Therefore, to present socially desirable responses, interviewees would tend to underreport their use of social media in the questionnaire survey.

Third, no demographic characteristic was found to be associated with over- and under-reporting of SNS use. Previous studies that covered more general population have found that age and household size are correlated with misreporting (Boase & Ling, 2013; Wonneberger & Irazoqui, 2013). Yet in this study, I only recruited college students, most of whom were of a similar age, living semi-independently, and unmarried. Therefore, the effect of demographics was not significant.

Last but not least, the findings point to no significant correlation between time spent on SNS and social life subjective well-being. However, there is a moderate positive correlation between time spent on SNS and fear of missing out. There are a few possible explanations. First and foremost, given that internal personal factors (e.g., personality traits, self-esteem, anxiety, etc.) were not controlled in this study, it is not possible to tell to what extent those factors might influence people's well-being, and whether the correlation between time spent on SNS and well-being would be affected by those factors. It is an important issue for future research to consider other potential mediators, such as social adaptability, loneliness, extraversion, etc. Second, according to the participants' feedback, nowadays, social media serves more than the communicative function. Indeed, time spent on social media does not mean time spent on communicating with people, which has been verified as a positive predictor of maintaining social capital and reaching better subjective well-being. In fact, even many errands are run on social media. Again, this study proves that the content or way of using social media is much more critical. Given that social media's function is no longer limited to communication, there is ample room for further progress in determining the relationships between the time spent on SNS for different purposes (e.g., entertainment, communication, payment, information acquisition, etc.) and well-being.

As mentioned above, many attempts have been made to improve data collection accuracy when studying people's online behaviour, including accessing server log data. Screen Time still has clear advantages, even comparing with log data. For example, Screen Time report covers a broader range of activities on mobile phones, while server log data only provide information about phone calls and text messages. Apparently, phone calls and short messages are no longer the primary means of communication, especially for the young generation. In fact, Screen Time would be a more apt reflection of the reality of people's daily social contact. Also, Screen Time data is easier to access. It is burdensome to request log data from mobile phone carriers on a daily basis. However, asking the participants for a screenshot is much more straightforward and easily practicable.

The limitations of the current study should be acknowledged. First, according to the participants' feedback, people are likely to have different SNS usage patterns on weekdays than during weekends due to differences in the allocation of study and leisure time. In the future, it is worth concerning the differentiation between weekday and weekend day "Screen Time" reporting and SNS use. This limitation could be better addressed by a longitudinal study, which would track the use of smartphones and social media during the week. Second, whether systemic or personal, there might be factors that make the application over- or under-report actual usage. For example, some participants reported that even though they had turned on the “Screen Time” function, the application failed to record user’s activities for some reason. As a result, they had to reset the user data and restart the questionnaire survey from the very beginning. Future studies might consider applying screening questions at the beginning of the survey to ensure that the tracking application is fully functional. Third, the use of college student samples limits the ability to generalize the findings in this study to other age groups. Previous studies have found that student samples may differ from the public, and student-nonstudent dimension may be a potential moderator when establishing the model (Henry, 2008). To address this concern, the investigation should be extended to a more general population in the future. Last but not least, only iPhone users participated in this study, while Android users’ daily behaviour on smartphones and social media were overlooked. Previous studies have shown that iPhone users were more likely than Android users to be female, younger, and have higher levels of emotionality (Shaw, Ellis, Kendrick, Ziegler, & Wiseman, 2016). These factors may have biased the data from the general population. In the future research, it is worth investigating to which extent do findings in this study may replicate in non-iPhone users.

Overall, “Screen Time” turns out to be a fruitful approach with countless possibilities in new media and communication studies. Since the “Screen Time” function provides us with so much valuable information, other indices can be applied in future studies, including mobile phone pick-up times and the number of notifications per hour. As people are investing increasing amounts of time on internet platforms and becoming more and more emotionally attached to related technologies, it is important to better understand what occurs in this virtual reality and find a proper balance between online and offline life.

## 5. Conclusions

This study managed to apply the “Screen Time” function on the most available and most used device in people’s everyday lives, the smartphone, as a measuring tool and discussed the relationship between time spent on SNS and people’s subjective well-being. Research results showed that “Screen Time” reporting is more reliable than a traditional self-reporting approach, especially for heavy social media users. The application-traced data helps to improve the accuracy of measurements and fend off unwanted under-reporting of usage. Therefore, “Screen Time” can be applied to further studies concerning individual online behaviour and well-being. In conclusion, this paper points toward the need to improve self-report measures that operationalize the intensity of digital technology use. Given that self-report measures are often used in influential computer-mediated communication studies, more efforts should be dedicated to understanding people’s recalling behaviour and examining possible factors that may lead to recall failure.

There has been a long-standing debate about the extent to which scientific research should be involved with the general public. On the one hand, it encompasses practices such as encouraging scholars to make their works accessible to society, whether amateur or professional. On the other hand, it indicates that scientific research should go back to our daily lives and care more about what is happening around us. Yet this study once again suggests that new technology *per se* is neither good nor bad. It is how people use it that makes the difference.

## Endnotes

1 The Chinese equivalent of LINE. WeChat is a mix of applications, which allows people to send instant message and post texts, pictures and short videos on *Moments*.

2 The Chinese equivalent of Twitter. Sina Weibo is a microblogging platform on which people can create profiles and upload multimedia content to their networks.

3 The Chinese equivalent of WhatsApp. QQ is an instant messaging application that offers many different services, including gaming, music, blogging, etc.

4 The Chinese equivalent of Rotten Tomatoes. On Douban, registered users can rate, record information, and create content related to films, books, music, recent events, and activities in Chinese cities.

5 A question-and-answer website where questions are created, answered, edited and organized by its registered users.

6 The Chinese equivalent of Reddit. Users can search for a topic-of-interest forum and post and interact with others in these forums. These forums cover a variety of topics, such as celebrities, films, books, comics, etc.

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