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The relationship between smartphone use and subjective well-being in rural China

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Abstract
Due to the popularization of the Internet in rural China, mobile Internet use has become an essential part of rural residents' lives and work. No studies, however, have investigated the potential effect of smartphone use on quality of life among rural residents in China. This study thus applies ordinary least squared, conditional quantile and instrumental variable techniques to survey data for 493 rural Chinese households to assess the impact of smartphone use (SU) on their subjective well-being (SWB). The results reveal an association between SU and increases in both life satisfaction and happiness that remains even after we adjust for possible endogeneity. The analysis also indicates that SU intensity is associated with lower levels of both SWB measures, especially when it exceeds 3 h per day. Quantile estimates further indicate that in both participation and intensity, SU has a much greater impact on SWB at the median level of the SWB distribution. Our multiple mediation results show that the positive SU–SWB linkage is partially mediated by both farm income and off-farm income. This may suggest that the local government should invest in Internet infrastructure to promote agricultural activities and develop specific rural services to boost farm income via better access to information of agricultural production and market networks. Mobile information and communication technologies can also provide more opportunities for rural entrepreneurship and innovation, in particular by motivating young farmers to actively engage in rural e-business ventures which can raise off-farm income.

Keywords Smartphone use · Life satisfaction · Happiness · Rural China

JEL Classification I31 · J30 · J33 · O33

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1 Introduction

Compared with 210 million in 2007, China had 829 million Internet users in 2018. Among them, mobile Internet users are the dominant (817 million), accounting for 98.6% of all such netizens nationwide [1], as well as the highest 2015 smartphone penetration rate (i.e. the proportion of smartphone users to total population), an estimated 68% versus an average 55% across European countries [2]. Not only have the advancement of mobile communication networks and the popularization of smartphones propelled the mobile Internet into every aspect of Chinese daily life [1], but mobile commercial applications have become the new driver of economic development. For example, in the first half of 2015, Internet users via smartphones made 267 million mobile payments, 270 million mobile purchases, and 168 mobile travel bookings, half-year increases of 26.9%, 14.5%, and 25.0%, respectively [3]. A major reason for this increase is that smartphones, unlike traditional mobile phones, offer enhanced functions like remote videos communication; distance learning (online education); and easy access to online information, entertainment, banking, and government services, all of which significantly improve and simplify everyday living [4].

Before the smartphones, the lack of computers prevented most rural residents in China from accessing the Internet, so it is not surprising that mobile phone usage, and particularly smartphones, is becoming increasingly important for this population. In addition to communication benefits, smartphones can generate income gains by facilitating the delivery of financial, agricultural, health, and educational services, enhancing agricultural production and marketing, stimulating job market participation, expanding social networks, and reducing household exposures to risks [5].

Up to the end of 2017, rural China had 209 million Internet users, accounting for 27% of the national netizens [6]. A recent report also claims that the use of mobile phones exceeds that of landline telephones in rural China, with over 92.9% mobile phones owners [7]. The proportion of China's rural Internet users using online payment has increased from 31.7% in 2016 to 47.1% in 2017 [6]. Meanwhile, 129 million rural netizens have purchased Internet financial products and utilization rate of Internet finance was 16.7% in 2017, compared with 13.5% in 2016 [6]. However, rural Internet users lag behind urban counterparts in the use of business and finance Apps. For instance, the urban–rural gap ranges from 20 to 25% in the use of Apps for online shopping, travel booking, online payment and Internet finance [6]. Some farmers even fear that this technology would bring about negative consequences mainly because they view the use of Apps (e.g. online financial services) as insecure [7]. Owning to the popularity of smartphones, mobile Internet applications have become an integral part of rural residents' lives and work. Smartphone use (SU) thus has major potential to boost the income levels of rural Chinese households [8], making this setting an interesting case for exploring the relationship between SU and subjective well-being (SWB) in a developing non-Western environment.

In developed countries, the effect of SU on SWB has been widely addressed. For example, Ohly and Latour [9] use survey data to show that among 1,714 working individuals in Germany, work-related SU in the evening is positively linked to psychological detachment (i.e. agreement that "In the evenings, I forget about work") and negatively related to a positive outcome (e.g. feeling active in the evenings). Similarly, drawing on the data from a diary study of 74 German employees covering ten working days, Gombert et al. [10] find that work-related SU impairs employees' psychological well-being. This finding is further reinforced by Rotondi and Stanca [4], who, using 2010–2014 data from the Italian Multipurpose Survey on Households, show that SU undermines the quality of face-to-face interactions, thereby dampening their positive impact on life satisfaction. Likewise, Kim et al. [11] confirm that, compared to normal SU, smartphone addiction is linked with an increased risk of depression and anxiety in South Korea, which is echoed by Lee et al. [12], Park and Lee [13] for South Korean university students.

Moreover, a study by Horwood and Anglim [14] shows that problematic SU is linked with lower levels of psychological well-being[1] among Australian university students. A similar study by Lee et al. [15] also shows that compulsive usage of smartphone is positively associated with certain psychological traits including locus of control, social interaction anxiety, materialism and the need for touch in Taiwan (province of China), where the smartphone penetration rate is closest to the average of developed countries among all the 47 countries [16]. The evidence is further supported by Elhai et al. [17] and David et al. [18] for the US, Hughes and Burke [19] for the UK, Kumcagiz and Gündüz [20] for Turkey, and Samaha and Hawi [21] for Lebanon. Nonetheless, although the majority of existing studies shed useful light on the SU–SWB relation in a Western setting, it is impossible to generalize their results to rural China whose different cultural, political, and social contexts are likely to result in different SWB determinants. To the best of our knowledge, we only identify three studies [22–24] that have revealed the negative association between problematic SU and SWB among Chinese university students.

Historically, for example, in communists or collectivist societies aspects such as in-group solidarity, religiosity, and national pride have been important drivers of SWB [25], whereas capitalist or individualistic societies have tended to cherish free choice and personal freedom [26]. Nevertheless, as Steele and Lynch's [27] analysis of 1990–2007 World Values Survey (WVS) data shows, although both individualist and collectivist factors predict SWB in China, individualist factors like income, employment status, and freedom of choice have become more important over time than collectivist factors, with household income being a particularly important predictor [28].

The aim of this study is, therefore, to assess the impact of SU on SWB in rural China. We extend the literature in five ways. First, our analysis uses unique recent survey data for 493 households in rural China. Second, in addition to employing standard ordinary least squares (OLS) and quantile regressions, we follow Rotondi and Stanca [4] by introducing an instrumental variable (IV) approach that addresses

[1] Horwood and Anglim [14] adopt Ryff's six psychological well-being domains, including positive relations, autonomy, environmental mastery, personal growth, purpose of life and self-acceptance.

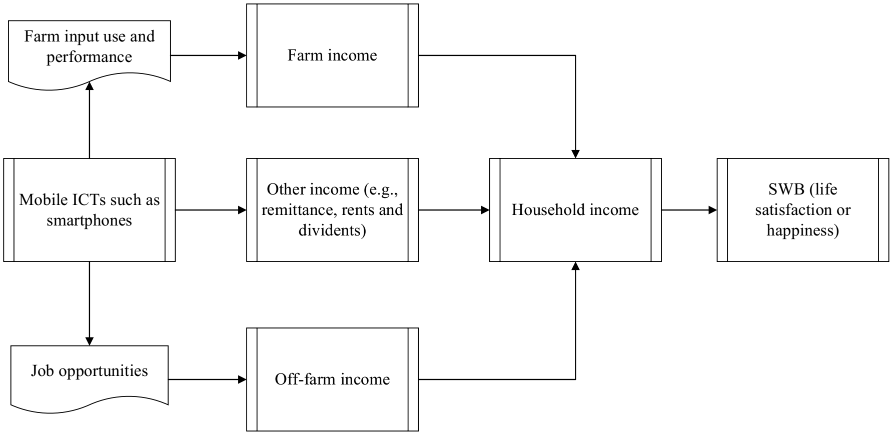

Fig. 1 Heuristic of potential mechanisms of mobile ICTs on SWB of rural residents

the potential endogeneity of SU, thereby shedding light on the causal relation between SU and SWB. Because SU is a self-selection process, both observed and unobserved heterogeneities may affect an individual's decision to use a smartphone [29, 30]. Failing to address such endogeneity issues could lead to biased estimate of the impact of SU on SWB. Third, we extend the prior work by adopting both life satisfaction and happiness as SWB measures to produce a more differentiated picture of the SU-SWB relation. Fourth, unlike prior studies that consider only the first-level digital divide (SU) [4], we employ both SU and SU intensity (measured in hours per day), using the latter as a proxy of the second-level digital divide. Our final contribution is the use of a multiple mediation technique [31, 32] that introduces farm income and off-farm income as intervening variables to identify their potential mediation in the SU–SWB association, which sheds light on the underlying pathways through which SU works on SWB.

The rest of the paper is organized as follows. We describe the heuristic of possible mechanisms of SU on the SWB of rural residents in Sect. 2. The data and methodologies used for the analysis are introduced in Sect. 3. The results are presented and discussed in Sect. 4. Section 5 presents conclusions, highlights possible policy implications and discusses limitations and future research directions.

2 The heuristic of possible mechanisms of SU on SWB

Figure 1 illustrates a simple heuristic of possible mechanisms through which mobile ICTs such as SU work on SWB of rural residents. Past research has shown that mobile ICTs directly affect farm production [33, 34], market transactions [35, 36], and decision-making of household heads regarding off-farm labor supply [37], thereby indirectly influencing farm income and off-farm income [30, 38]. As demonstrated in Fig. 1, mobile ICTs use may boost farm income via improving farm input use and performance because it would facilitate communications between farmers and input/output dealers and increase income for off-farm workers through finding better job opportunities [30]. As emphasized by Ma et al. [30], household income encompasses not only farm income and off-farm income, but income from other sources such as rents, dividends, and annuities. Thus, we also underscore that, besides farm income and off-farm income, the use of mobile ICTs would directly affect household income via other household activities such as remittances, rents and dividends [38, 39]. It should be noted that household income is a key predictor for SWB of rural residents [40, 41]. With the exception of Ma et al. [30], all these prior studies are done in rural India and African countries. Based on the heuristic illustrated in Fig. 1, we assume that SU affects farm income, off-farm income and income from other sources, and then total household income, thereby maximizing households' utility (denoted by SWB measures of rural residents in our case—life satisfaction and happiness).

Drawing on past research on the impact of ICTs on household income and our heuristic, our key null hypotheses are the following: (1) SU participation is associated with increased SWB levels whilst the length SU is linked with decreased SWB levels; (2) SU affects life satisfaction and happiness differently since life satisfaction (a long-term measure) captures thoughts and feelings of life but happiness (a short-term measure) refers to the emotional quality of everyday experience [42]; and (3) the SU-SWB relation is mediated by farm income and off-farm income. The analysis of these hypotheses provide answers to important policy questions related to rural China, namely what is the impact of SU on rural households' SWB, and what are the potential mechanisms through which SU operates on SWB.

3 Data and methods

3.1 Study sample

The household survey, conducted in rural China in January 2017, encompassed a range of information, including household characteristics, asset ownership, cooperative membership, demographic and socioeconomic factors, smartphone use, and the SWB of the household head.

The selection of both smartphone users and non-users employed a multistage sampling procedure that began with the choice of three provinces that differ greatly in geographic and socioeconomic conditions: Gansu, a less economically developed province in western China, Henan, a central province dominated by agriculture, and Shandong, an eastern industrialized province. The researchers then randomly selected one city from each province (Dingxi, Sanmengxia, and Heze, respectively) and three towns (specifically, Yujing, Yaodian and Longjin in Dingxi; Guxian, Jiaoyangzhen and Zhucun in Sanmenxia; Liulin, Zhangfeng and Taomiao in Heze) in each city. Finally, one village in each town and about 40–60 farmers in each village were randomly selected [30]. For the survey itself, well-trained enumerators, recruited from local universities in each province and proficient in both Mandarin and the local language, conducted face-to-face interviews with a total of 493 households in and around the selected villages.

3.2 SWB measures

Whereas happiness is a measure of hedonic well-being that captures the emotional quality of everyday experience, life satisfaction refers to thoughts and feelings about life [42]. These two aspects may thus serve as a long-term and short-term measure of SWB, respectively (see, e.g. Pénard et al. [43]). In this study, to generate a more differentiated picture of the SU–SWB relation, we employ both indicators, assessed by the survey questions "How satisfied are you with your life?" and "How happy are you?" (measured on a 10-point scale from 1 = very unsatisfied/very unhappy to 10 = very satisfied/very happy).

3.3 Smartphone use

To measure SU, we use two different approaches to explore the first-level and second-level digital divides; namely, SU (1 = yes and 0 = no) and SU intensity (hours per day). The intensity measure is based on the question, "How many hours per day do you use the smartphone?". In addition, to detect a possible nonlinear SU–SWB relationship, we define dummy variables for SU intensity by recoding it into four groups: $0 < \text{SU intensity} < 1$, $1 \leq \text{SU intensity} < 2$, $2 \leq \text{SU intensity} < 3$, $\text{SU intensity} \geq 3$. We designate 0–1 h per day as our reference group.

3.4 Individual and household characteristics

The individual characteristics considered are the age, gender, and education level of the household head, with gender a binary variable equal to 1 if the respondent is male (0 otherwise) and education level a continuous variable proxied by years of schooling. The household characteristics are log-transformed total household income and household size.

3.5 Estimation strategies

First, we employ the standard OLS estimation technique to investigate the association between SU and SWB. Since OLS estimation is a mean-based regression, it does not allow us to capture the impact of SU at different quantiles of the SWB distribution. We thus use a quantile regression approach. Third, considering the potential endogeneity of the SU variable, we introduce a two-stage predictor substitution estimator to investigate the causal relationship between SU and SWB. Finally, we adopt a multiple mediation technique to disentangle the indirect effects of SU on SWB (namely farm income and off-farm income) from the direct effect of SU on SWB.

3.5.1 Ordinary least squares regressions

Although the 10-point scaling of our life satisfaction and happiness measure might suggest a latent variable estimation method as the most appropriate, because the bias introduced by an OLS analysis is relatively small [44], we adopt the standard OLS regression method applied in the majority of SWB studies (e.g. [45]). More specifically, we apply an OLS estimation based on the following model:

$$SWB_i = \beta_0 + \beta_1 SU_i + \beta_2 X_i + \beta_3 F_i + \beta_4 P_i + \omega_i \tag{1}$$

where SWB_i denotes the subjective well-being of individual i in terms of life satisfaction and happiness, and SU_i denotes the individual's SU (represented by a dummy for SU and a vector of dummies for SU intensity, with 0–1 as the reference group). X_i is a vector of individual i's characteristics, and F_i is a vector of household characteristics. P_i is a vector of provincial dummies (with Gansu as the reference province); β_0 is a constant. β_1, β_2, β_3 and β_4 are parameters to be estimated. In particular, β_1 captures the effect of SU on individuals' SWB. ω_i is an error term.

3.5.2 Quantile regression

As the distribution of SWB such as life satisfaction or happiness is skewed [46, 47], mean-based methods such as OLS will result in under- or overestimated effects of SU on SWB or even failure to identify the heterogeneous effects [48]. As such, quantile regression might be preferable to represent how SWB responds to changes in covariates [49]. Moreover, quantile regression is a useful tool for identifying extreme effects in the SWB distribution, thereby providing a more comprehensive picture of the effects of the covariates on SWB measures [46]. Furthermore, going beyond the mean is important with regard to individual-specific rates of hedonic adaptation [47]. Hedonic adaptation refers to the process that, after experiencing life events (e.g. getting married, death of spouse) which may initially cause a significant change in SWB, most people appear to revert toward their previous baseline level of SWB [50]. Thus, to assess whether SU has a different impact across the distribution of individual SWB (conditional on control variables), we estimate the following quantile regression model at the 25th, 50th, and 75th percentiles using the same specifications as in the OLS model:

$$SWB_i^q = \eta_1^q SU_i + \eta_2^q X_i + \eta_3^q F_i + \eta_4^q P_i \tag{2}$$

where η_1^q, η_1^q, η_1^q and η_1^q are parameters to be estimated, with q denoting different quantile levels. Among them, η_1^q is the key parameter of interest. In contrast to mean-based OLS regression, quantile regressions allow for the SU impact to differ over the quantiles of individual SWB.

3.5.3 Instrumental variable (IV) estimation

SU measures are subject to endogeneity for two main reasons: individual unobserved heterogeneity when SU and SWB are simultaneously affected by unobserved personality traits like extraversion or self-esteem [4] and/or reverse causality when happier individuals are more prone to use the smartphone. Thus, to identify a causal relationship between SU and SWB, we also estimate a two-stage instrumental variable (IV) model like that of Rotondi and Stanca [4], which uses a variable representing the SU status of relatives or friends as an instrument. This variable is based on the question: "are your relatives/friends using smartphones?" with the respondent' response of 1 = yes and 0 = no. The rational for using this variable as an instrument is that farmers' decision to use the smartphones is likely to be affected by their relatives/friends' SU behaviours due to so-called peer effects. However, the use of this variable as an instrument assumes that farmers' SWB cannot be directly affected by their relatives/friends' SU status. We used a Pearson correlation analysis to test the validity of the IV. The results reveal that the variable representing the relatives/friends' SU is positively and significantly associated with individual's SU, but it is not significantly associated with individual SWB, confirming the validity of the IV employed in this study. Since our endogeneous variable—SU—is binary, we adopt a two-stage predictor substitution, which is an extension (to nonlinear models) of the commonly-used linear two-stage least squares estimator [51]. We estimate the following model (i.e. the second-stage equation of the IV model):

$$SWB_i = \xi_0 + \xi_1 SU_i^* + \xi_2 X_i + \xi_3 F_i + \xi_4 P_i + \delta_i \tag{3}$$

where SU_i^* is the predicted value of the endogenous variable of individual SU. To obtain SU_i^*, we estimate the first-stage equation using a probit approach as follows:

$$SU_i = \varphi_0 + \varphi_1 Z_i + \varphi_2 X_i + \varphi_3 F_i + \varphi_4 P_i + \mu_i \tag{4}$$

where Z_i is the instrumental variable that represents SU status of an individual's relatives or friends, and μ_i is an error term.

3.5.4 Multiple mediation analysis

As highlighted by Preacher and Hayes [31], the statistical analysis of mediation effects has become a commonly used technique in behavioural science and psychology. Mediation exists when a predictor affects a dependent variable indirectly through at least one mediator [31] and thus provides an avenue of accounting for the mechanism by which one variable influences another [52]. We use bootstrapping-based multiple mediations [31] to identify the indirect effects of our mediators (farm income and off-farm income) on the SU–SWB relationship. Such an analysis captures indirect effects and also disentangles individual mediating effects among several mediators [32]. In particular, as Preacher and Hayes [31] stress, in a multiple mediation setting, a specific indirect effect via a mediator is not the same as the indirect effect through this mediator alone. The following set of equations denotes multiple mediation analysis in which an independent variable X affects a dependent variable Y via two mediators M_1 and M_2 [52]:

$$Y = \theta_1 + cX + \varepsilon_1 \tag{5}$$

$$Y = \theta_2 + c'X + b_1 M_1 + b_2 M_2 + \varepsilon_2 \tag{6}$$

$$M_1 = \theta_3 + a_1 X_1 + \varepsilon_3 \tag{7}$$

$$M_2 = \theta_4 + a_2 X_2 + \varepsilon_4 \tag{8}$$

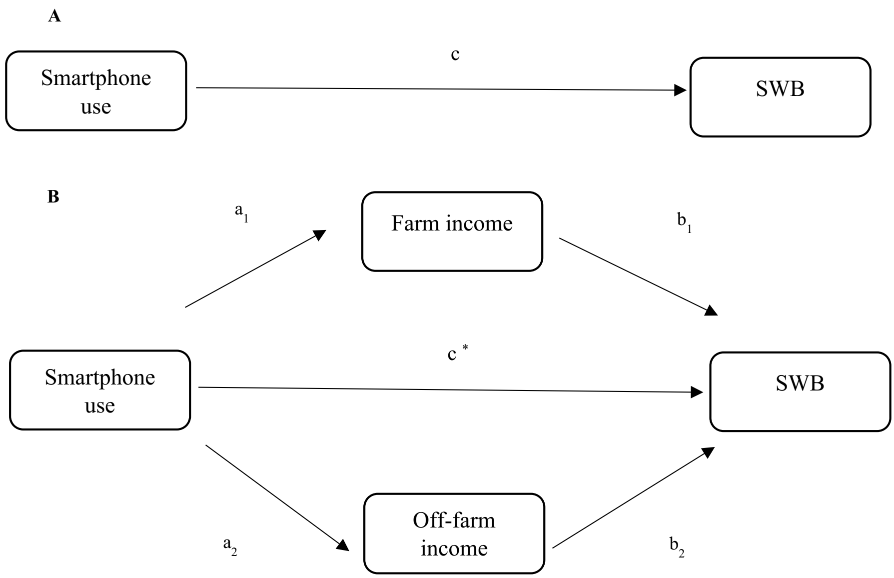

Fig. 2 A multiple mediation design

where θ_1, θ_2, θ_3 and θ_4 represent intercepts for Eqs. (5), (6), (7) and (8), respectively. c represents the coefficient relating the independent variable X to the dependent variable Y. c' is the coefficient relating the independent variable X to the dependent variable Y adjusted by the mediators M_1 and M_2. b_1 and b_2 are the coefficients of the mediators M_1 and M_2 to the dependent variable Y adjusted by the independent variable X, and a_1 and a_2 denote the coefficients relating the independent variable X to the mediator M_1 and M_2, respectively. ε_1, ε_2, ε_3 and ε_4 are residual terms for the four equations. As highlighted by MacKinnon et al. [52], the mediation equation could also incorporate linear and nonlinear effects, as well as interactions between X, M_1 and M_2.

In the multiple mediation design used in our study, the total effect of SU on SWB is via path c (see Fig. 2A). Figure 2B illustrates the direct effect of SU on SWB via path c^* and its indirect effects through the two potential mediators: farm income and off-farm income. Because the specific indirect effect of SU on SWB via a mediator is the product of the two unstandardized paths relating SU to SWB through this mediator, the specific indirect effects for farm income and off-farm income are a_1b_1 and a_2b_2, respectively. Accordingly, the total indirect effect of SU on SWB is the sum of the two indirect effects, meaning that the total effect (c) of SU on SWB is the sum of the direct effect (c^*) and the total indirect effects via those two mediators. Using this multiple mediation analysis, we are able not only to identify the total indirect effect associated with farm income and off-farm income but also to test hypotheses on each mediator in our multiple mediation context. As MacKinnon et al. [52] emphasize, partial mediation exists when the coefficient for direct effect is statistically significant and there is significant mediation.

To generate confidence thresholds for the specific indirect effects [53], we bootstrap the sample distribution of specific and total indirect effects by taking a sample size n from the original sample with replacement and then repeating this process m times. Because the recommendation is $m \geq 1000$, we use 5000 iterations [54, 55]. This process also identifies the upper and lower cutoffs of the confidence intervals (CI) for both the specific and the total indirect effect. Additionally, our relatively small sample size ($n = 493$) means that the underlying normality assumption of the sampling distribution may not hold, and we thus bootstrap the percentile (P), bias-corrected (BC), and bias-corrected and accelerated (BCa) 95% confidence intervals (CI), simultaneously [56].[2] In Monte Carlo comparisons among the various methods, the BC bootstrap intervals tend to perform slightly better than the other two (percentile and BCa) [55], we therefore use this approach to confirm the significance of mediation. It should be noted that the results are deemed significant when the confidence intervals do not cross zero [54, 55].

4 Results

4.1 Descriptive statistics

As Table 1 shows, the household heads surveyed are predominantly male (83.6%), aged on average around 47, and with 6.78 average years of schooling (slightly above the primary school level of 6 years). On average, they reported spending around 1.77 h per day on smartphone use. Although the mean values for their life satisfaction and happiness are 6.88 ($SD = 1.93$) and 6.86 ($SD = 1.88$), respectively, closer examination of the life satisfaction and happiness distributions (see Fig. 3) reveals that the proportion reporting a 10 in life satisfaction is slightly higher (13%) than that reporting a 10 in happiness (10%). We also note that in our sample, the SU is 65%, somewhat lower than the 68% smartphone penetration rate in all of China in 2015 [2], possibly because we are focusing on specific rural areas only.

4.2 Smartphone use and SWB

4.2.1 Smartphone use and SWB

Table 2 reports the OLS estimates of the SU–SWB relation, which indicates that SU is positively and significantly associated with SWB irrespective of whether life satisfaction or happiness is used as the proxy (columns 1 and 2, respectively). Specifically, SU is related to a 0.69 or 0.40 increase in life satisfaction or happiness, respectively. This observation is well in line with Rotondi and Stanca [4] for Italy, indicating that SU is positively associated with life satisfaction. The SU difference in effect size of life satisfaction and happiness is attributable to the fact that life

[2] A detailed discussion of bias corrected (BC) and bias corrected and accelerated (BCa) confidence intervals is available in Efron [56].

Table 1 Descriptive statistics

Variable	Obs.	Mean	SD	Min	Max
Dependent variables					
Life satisfaction (1–10)	493	6.884	1.929	1	10
Happiness (1–10)	493	6.862	1.880	1	10
Key independent variable					
Smartphone use (1 = yes, 0 = no)	493	0.647	0.478	0	1
Smartphone use intensity (h/day)	319	1.769	1.509	0	10
Individual and household controls					
Age of household head	493	46.787	10.323	20	73
Years of schooling of household head	493	6.779	2.760	0	16
Gender of household head	493	0.836	0.371	0	1
Log(household total income)	493	10.678	0.650	7.601	14.509
Household size	493	4.552	1.447	1	11
Smartphone use of relatives or friends (IV)	493	0.963	0.188	0	1
Province					
Gansu	493	0.327	0.469	0	1
Henan	493	0.345	0.476	0	1
Shandong	493	0.329	0.470	0	1

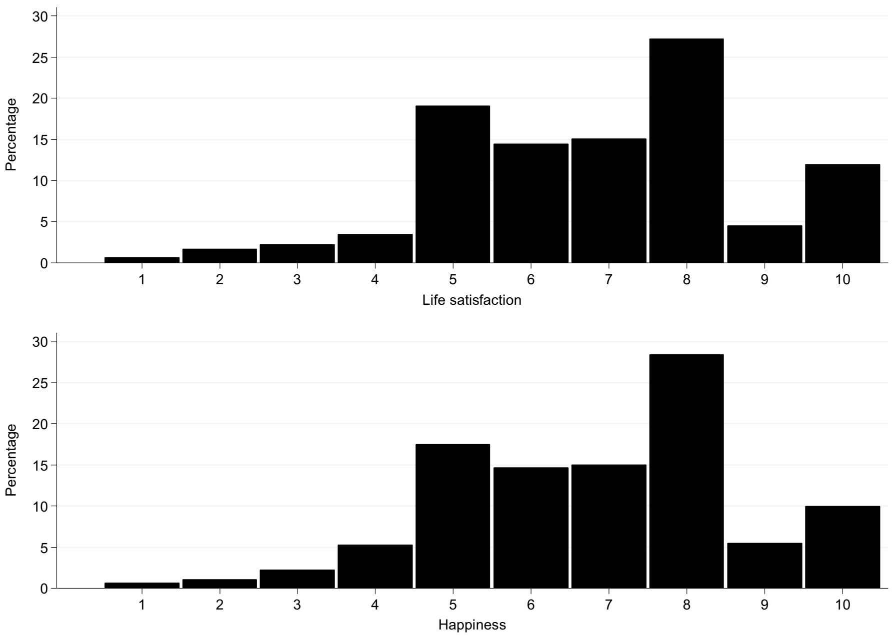

Fig. 3 Distributions of life satisfaction and happiness

Table 2 OLS estimates for the impact of smartphone use on SWB

	Life satisfaction (1)	Happiness (2)
Smartphone use	0.694***	0.396**
	(0.208)	(0.201)
Age	−0.081	−0.090*
	(0.053)	(0.051)
Age squared	0.001	0.001
	(0.001)	(0.001)
HH male	−0.319	−0.386*
	(0.221)	(0.207)
HH years of schooling	0.010	0.001
	(0.033)	(0.032)
Log (household income)	1.010***	1.098***
	(0.153)	(0.149)
Household size	−0.112**	−0.109**
	(0.054)	(0.052)
Henan	−0.225	−0.031
	(0.210)	(0.214)
Shandong	0.305	0.374**
	(0.191)	(0.188)
N	493	493
Adj. R^2	0.197	0.198

The dependent variables are the 10-point-scale measures of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). The controls include smartphone use participation (1 = yes, 0 = no), individual characteristics (including age, age squared, years of schooling), household size and translog household total income, and provincial dummies (with Gansu as the reference province). Robust standard errors are in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

satisfaction is a measure of evaluative well-being representing thoughts and feelings about life whilst happiness is a proxy of hedonic well-being capturing the emotional quality of everyday experience [42]. More important, as highlighted by Pénard et al. [43], life satisfaction serves as a long-term self-assessment, but happiness is a short-term measure of SWB. Males are less likely to report happiness than females, which is a common finding in the SWB literature and also echoed by Lei et al. [57] for China and especially Knight et al. [40] for rural China. As also reported by Zhang and Yang [28] for China, lower SWB is associated with a larger household. However, increased life satisfaction or happiness is linked to a high household income, suggesting that income is an important predictor of individual SWB.[3] This finding is consistent with those extant studies for China [40, 41, 58]. The positive and statistically significant coefficient of Shandong variable (column 2 of Table 2) suggests

[3] As a robustness check, to capture possible differences in economic development and infrastructures across villages, we also introduced village-level dummies and the results (Table 10 in the Appendix)

that compared with household heads in Gansu (reference group), those in Shandong are much happier. This observation can be partially explained by the fact Gansu is an economically less developed province in western China whereas Shandong is an eastern industrialized province, and people in rich regions are, on average, happier than those in poor regions. The finding also confirms the presence of geographically fixed effects that may also affect SWB.

Since OLS estimates focus on the effect of explanatory variables at the mean of the conditional distribution of SWB and the distribution of SWB measure is generally skewed, we introduce a quantile regression technique. We report the quantile estimates of the SU–SWB association in Table 3, which shows that SU is uniformly and positively associated with an increase in life satisfaction at all three percentiles. The magnitudes do vary, however, with the largest effect at the median level of life satisfaction (25th: 0.38; 50th: 1.00 and 75th: 0.71; Panel A, columns 1–3). SU is also related to an increase in happiness except at the 25th percentile (Panel B, columns 1–3). Also consistently evident is the positive association between SWB and household income as opposed to the negative correlation between SWB and household size. In particular, for both life satisfaction and happiness, we consistently find the largest effect of household income on individual SWB at the lower distribution (25th) of SWB but a declining importance of household income with increasing quantiles of the SWB distributions (life satisfaction: 25th: 1.345; 50th: 0.954 and 75th: 0.629; happiness: 1.482; 50th: 1.146 and 75th: 0.736). This may suggest that, although income boosts individual life satisfaction or happiness, truly life-satisfied or happy individuals are less dependent on income and income mostly matters for those at the lower part of the SWB distribution. This finding can only be discernable in our quantile regressions and is glossed over in the mean-based regressions such as OLS mainly because the strong association with income in the lower quantiles of the SWB distribution compensates this in the mean values [46]. Such heterogeneity in the income-SWB link is well in line with Binder and Coad [46] for the UK. Interestingly, a U-shaped relation is observable between age and SWB at the median level of the SWB distribution, one that minimizes at around age 46 for life satisfaction and age 56 for happiness. This finding is mirrored by international literature [45] and those for China [40, 57, 58], confirming that there exists a convex link between age and SWB and a typical individual's happiness or life satisfaction reaches its minimum in middle age.[4]

4.2.2 Smartphone use intensity and SWB

The results for the second-digital divide's effect on SWB indicate that SU intensity, in particular, ≥ 3 h per day, is significantly and negatively associated with

Footnote 3 (continued)
reveal that SU remains significantly associated with life satisfaction. For happiness, the coefficient is positive but insignificant.

[4] A detailed discussion of related theories on the U-shape between age and SWB is available in Blanchflower and Oswald [34].

Table 3 Quantile estimates for the impact of smartphone use on SWB

	25th (1)	50th (2)	75th (3)
Panel A: Life satisfaction			
Smartphone use	0.380*	1.000***	0.707***
	(0.197)	(0.219)	(0.253)
Age	−0.116	−0.091**	−0.038
	(0.073)	(0.045)	(0.067)
Age squared	0.001	0.001*	0.000
	(0.001)	(0.000)	(0.001)
HH male	−0.347	−0.542**	−0.174
	(0.257)	(0.212)	(0.332)
HH years of schooling	0.020	0.024	0.030
	(0.035)	(0.033)	(0.036)
Log (household income)	1.345***	0.954***	0.629***
	(0.152)	(0.181)	(0.121)
Household size	−0.085**	−0.115**	−0.134*
	(0.037)	(0.056)	(0.071)
Henan	−0.364	−0.361	0.124
	(0.297)	(0.271)	(0.288)
Shandong	0.289	0.018	0.479*
	(0.309)	(0.189)	(0.277)
N	493	493	493
Pseudo R^2	0.151	0.148	0.060
Panel B: Happiness			
Smartphone use	0.197	0.522*	0.350**
	(0.231)	(0.269)	(0.162)
Age	−0.177**	−0.111**	−0.042
	(0.084)	(0.047)	(0.052)
Age squared	0.002*	0.001*	0.000
	(0.001)	(0.001)	(0.001)
HH male	−0.464*	−0.616**	−0.076
	(0.255)	(0.281)	(0.147)
HH years of schooling	−0.013	−0.019	0.015
	(0.041)	(0.038)	(0.023)
Log (household income)	1.482***	1.146***	0.736***
	(0.132)	(0.166)	(0.103)
Household size	−0.116**	−0.110*	−0.129***
	(0.051)	(0.065)	(0.043)
Henan	−0.028	−0.376	0.395*
	(0.284)	(0.299)	(0.226)
Shandong	0.381	0.031	0.375***
	(0.294)	(0.222)	(0.134)

Table 3 (continued)

	25th (1)	50th (2)	75th (3)
N	493	493	493
Pseudo R^2	0.156	0.127	0.051

The dependent variables are the 10-point-scale measures of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). The controls include smartphone use participation (1 = yes, 0 = no), individual characteristics (including age, age squared, years of schooling), household size and translog household total income, and provincial dummies (with Gansu as the reference province). Robust standard errors are in parentheses

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4 OLS estimates for the impact of smartphone use intensity on SWB

	Life satisfaction (1)	Happiness (2)
Smartphone use intensity: 1–2 h/day	−0.238	−0.508**
	(0.256)	(0.258)
Smartphone use intensity: 2–3 h/day	−0.199	−0.297
	(0.256)	(0.262)
Smartphone use intensity: ≥ 3 h/day	−1.283***	−1.075***
	(0.316)	(0.339)
Age	−0.119*	−0.134**
	(0.061)	(0.059)
Age squared	0.001	0.001*
	(0.001)	(0.001)
HH male	−0.290	−0.214
	(0.277)	(0.266)
HH years of schooling	0.032	0.029
	(0.043)	(0.043)
Log (household income)	1.132***	1.243***
	(0.184)	(0.197)
Household size	−0.183**	−0.166**
	(0.078)	(0.073)
Henan	−0.259	−0.036
	(0.263)	(0.268)
Shandong	0.024	0.179
	(0.247)	(0.247)
N	319	319
Adj. R^2	0.216	0.228

The dependent variables are the 10-point-scale measures of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). The controls are dummy for smartphone use intensity (< 1 h/day [reference group], 1–2 h/day, 2–3 h/day, and ≥ 3 h/day), individual characteristics (including age, age squared, years of schooling), household size and translog household total income, and provincial dummies (with Gansu as the reference province). Robust standard errors are in parentheses

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

SWB irrespective of whether life satisfaction or happiness is used (Table 4, columns 1–2). However, regarding the two SWB measures, there exist differences in the effect sizes (for SU intensity ≥ 3 h per day, life satisfaction: -1.283; happiness: -1.075). Once again, this may emphasize the fact that SWB can be captured by diverse well-being indices and, therefore, it is quite important to introduce both hedonic and evaluative measures of SWB such as happiness and life satisfaction in our case. Our finding may also imply that, in addition to addressing the first-level digital divide, it is also important for researchers to explore SWB's association with the second-level digital divide. Similar to the results from the first-level digital divide (SU) based on OLS estimates, we also confirm that household income is an essential predictor for individual SWB, irrespective of life satisfaction or happiness.

Table 5 reports the quantile estimates for the association between SU intensity and SWB, which, like the OLS results, suggest that long hours of SU reduce life satisfaction at all three percentiles, with the largest impact at the median level of the distribution (Panel A, columns 1–3). Such is also the case for happiness except at the 25th percentile. It is also worth noting that a SU intensity of 1–2 h per day is also negatively associated with happiness, especially at the median and upper end of the distribution (Panel B, columns 1–3), which differs from the results for life satisfaction. This difference might imply that happiness and life satisfaction capture different aspects of SWB: the former is a short-run hedonic measure whilst the latter is a long-run self-assessment of evaluative well-being. In addition, similar to the results from the first-level digital divide, we also identify a decreasing importance in household income with increasing quantiles of both life satisfaction and happiness distributions (life satisfaction: 25th: 1.532; 50th: 0.926 and 75th: 0.806; happiness: 1.591; 50th: 1.103 and 75th: 0.820), implying that household income has the largest effect among the least happy or life-satisfied individuals, although income is uniformly and positively associated with both SWB measures.

4.3 Endogeneity

As Table 6 shows, the first-stage IV estimates indicate a significant association between the instrument and individual SU (Panel A, columns 1–2), while the first-stage *F* test results call for rejection of the null hypothesis of under-identification. Our first-stage results justify our assumption that individuals are more willing to own and use a smartphone if this technology is more widespread among their acquaintances such as relatives or friends. The second-stage results then confirm that SU increases individual SWB, regardless of whether the estimation is based on life satisfaction or happiness (Panel B, columns 1–2). It should be noted, however, that these IV results are much larger than the OLS results in Table 2.

Table 5 Quantile estimates for the impact of smartphone use intensity on SWB

	25th (1)	50th (2)	75th (3)
Panel A: Life satisfaction			
Smartphone use intensity: 1–2 h/day	−0.391	−0.141	−0.300
	(0.395)	(0.316)	(0.266)
Smartphone use intensity: 2–3 h/day	−0.398	−0.203	−0.190
	(0.408)	(0.302)	(0.270)
Smartphone use intensity: ≥3 h/day	−1.131**	−1.721***	−1.069**
	(0.462)	(0.349)	(0.458)
Age	−0.078	−0.099*	−0.081
	(0.144)	(0.060)	(0.062)
Age squared	0.000	0.001	0.001
	(0.002)	(0.001)	(0.001)
HH male	−0.130	−0.282	−0.148
	(0.372)	(0.224)	(0.275)
HH years of schooling	−0.011	0.040	0.073
	(0.065)	(0.034)	(0.045)
Log(household income)	1.532***	0.926***	0.806***
	(0.220)	(0.186)	(0.221)
Household size	−0.191**	−0.245***	−0.274***
	(0.094)	(0.069)	(0.083)
Henan	−0.279	−0.507*	−0.143
	(0.382)	(0.272)	(0.401)
Shandong	−0.085	−0.220	0.106
	(0.381)	(0.252)	(0.248)
N	319	319	319
Pseudo R^2	0.193	0.128	0.102
Panel B: Happiness			
Smartphone use intensity: 1–2 h/day	−0.572	−0.599**	−0.939***
	(0.376)	(0.295)	(0.276)
Smartphone use intensity: 2–3 h/day	−0.178	−0.455	−0.551**
	(0.431)	(0.318)	(0.266)
Smartphone use intensity: ≥3 h/day	−0.770	−1.599***	−0.892*
	(0.527)	(0.373)	(0.485)
Age	−0.183*	−0.119	−0.038
	(0.107)	(0.074)	(0.043)
Age squared	0.002	0.001	0.000
	(0.001)	(0.001)	(0.000)
Male	−0.206	−0.130	0.096
	(0.378)	(0.268)	(0.338)
Years of schooling	−0.053	0.008	0.041
	(0.068)	(0.043)	(0.046)
Log(household income)	1.591***	1.103***	0.820***
	(0.270)	(0.227)	(0.229)

Table 5 (continued)

	25th (1)	50th (2)	75th (3)
Household size	−0.142**	−0.222***	−0.278***
	(0.058)	(0.041)	(0.068)
Henan	−0.049	−0.304	0.511
	(0.489)	(0.295)	(0.343)
Shandong	0.260	−0.109	0.354*
	(0.452)	(0.245)	(0.204)
N	319	319	319
Pseudo R^2	0.203	0.141	0.084

The dependent variables are the 10-point-scale measures of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). The controls include individual characteristics (including age, age squared, years of schooling), household size and translog household total income, and provincial dummies (with Gansu as the reference province). Robust standard errors are in parentheses

*$p<0.1$, **$p<0.05$, ***$p<0.01$

4.4 Mechanisms

Our multiple mediation analysis examines the extent to which the SU–SWB link is explainable by specific mediators. As Table 7 reveals, the total effect of SU on life satisfaction and happiness is significant, although the magnitudes differ (see columns 1 and 3; 1.241 for life satisfaction; 1.015 for happiness). After adjusting for farm income and off-farm income, however, SU remains significantly and positively correlated with both life satisfaction and happiness (see columns 2 and 4; 0.948 for life satisfaction; 0.713 for happiness), implying that SU still has direct effects on SWB. It also suggests that, in rural China, both farm income and off-farm income are important predictors for rural residents' SWB.

Because of the potential biases from the point estimations in Table 7, we introduce a bootstrapping approach within a multiple mediation context. The results, shown in Tables 8 and 9, indicate that the total indirect effects and the indirect effects for the mediator of off-farm income are significant for both life satisfaction and happiness, implying that the models are partially mediated by the introduction of farm income and off-farm income. Specifically, the total indirect effect of the mediators on the SU-life satisfaction relation is significant, as shown by Table 8 in which the lower and upper levels of the BC 95% confidence intervals (LLCI and ULCI) are 0.0137 and 0.1852, respectively. Regarding the SU-happiness association, the LLCI and ULCI are 0.1531 and 0.4790, respectively (Table 9). In addition, it is worth noting that the direct effects of SU participation on both life satisfaction and happiness are also significant, with coefficients of 0.948 and 0.713, respectively (columns 2 and 4 in Table 7). However, a more in-depth examination of the specific indirect effects of our two mediators reveals both significant indirect effects for farm income (life satisfaction: LLCI (BC) = 0.0137, ULCI (BC) = 0.1852; happiness: LLCI (BC) = 0.0163, ULCI

Table 6 IV estimates for the impact of smartphone use on SWB

	Life satisfaction (1)	Happiness (2)
Panel A: First stage estimation of IV appraoch		
IV: Smartphone use of relatives/friends	0.731**	0.731**
	(0.386)	(0.386)
Panel B: Second stage estimation of IV appraoch		
Smartphone use	1.872***	1.667***
	(0.587)	(0.568)
Age	0.086	0.057
	(0.074)	(0.072)
Age squared	0.001	0.001
	(0.001)	(0.001)
HH male	−0.456	−0.514*
	(0.225)	(0.218)
HH years of schooling	−0.090	−0.092
	(0.053)	(0.046)
Log(household income)	−0.177	0.004
	(0.431)	(0.417)
Household size	0.0005	−0.007
	(0.067)	(0.065)
Henan	−0.769**	−0.533**
	(0.279)	(0.270)
Shandong	−0.185	−0.076
	(0.266)	(0.257)
First stage *F* test	14.19***	15.16***
Adjusted R^2	0.194	0.206
N	493	493

The dependent variables are the 10-point-scale measures of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). The controls include individual characteristics (including age, age squared, years of schooling), household size and translog household total income, and provincial dummies (with Gansu as the reference province). The instrumental variable is the smartphone use of relatives or friends. For the sake of simplicity, coefficients estimates of other control variavles in the first stage estimation of the IV approach are not reported. Heteroscedasticity-robust standard errors are in parentheses

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

(BC) = 0.1793) and off-farm income (life satisfaction: LLCI (BC) = 0.1066, ULCI (BC) = 0.3823; happiness: LLCI (BC) = 0.1178, ULCI (BC) = 0.4038).

Table 7 OLS estimates for smartphone use and SWB

	Life satisfaction (1)	Life satisfaction (2)	Happiness (3)	Happiness (4)
Smartphone use	1.241***	0.948***	1.015***	0.713***
	(0.210)	(0.213)	(0.205)	(0.205)
Age	−0.032	−0.067	−0.035	−0.071
	(0.059)	(0.056)	(0.058)	(0.056)
Age squared	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Male	−0.082	−0.362	−0.138	−0.423*
	(0.240)	(0.250)	(0.225)	(0.231)
Years of schooling	0.017	−0.004	0.014	−0.008
	(0.036)	(0.035)	(0.035)	(0.034)
Log (farm income)		0.389***		0.389***
		(0.093)		(0.093)
Log (off-farm income)		0.699***		0.725***
		(0.124)		(0.125)
Household size	0.006	−0.073	0.015	−0.066
	(0.060)	(0.058)	(0.058)	(0.055)
Henan	−0.183	−0.256	−0.027	−0.112
	(0.229)	(0.241)	(0.232)	(0.245)
Shandong	0.561***	0.010	0.593***	0.019
	(0.194)	(0.227)	(0.189)	(0.226)
N	439	439	439	439
Adj. R^2	0.129	0.208	0.105	0.195

The dependent variables are a 10 point-scale measure of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). Controls include individual characteristics (including age, age squared, years of schooling), household size and translogged farm income and off-farm income, and provincial dummies (Gansu as the reference province). Robust standard errors are in parentheses

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

5 Conclusion and discussions

5.1 Conclusion

By using unique survey data from rural China to analyze the SU–SWB relation, this study extends the extant literature to encompass the context of a non-Western developing nation. It also incorporates both life satisfaction and happiness measures of SWB and adopts a novel combination of the first-level and second-level digital divides to measure SU. Not only does this combined approach facilitate a thorough assessment of the SU-SWB linkage in rural China, it also contributes important insights to the general body of knowledge on SU and SWB.

Table 8 Mediation of the effect of SU on life satisfaction (using 5000 bootstrap samples)

Mediators	Observed		Bootstrap	95% Confidence intervals		
	Coef.	Bias	SE	Lower	Upper	
Farm income	0.0650	− 0.0003	0.0495	− 0.0221	0.1730	(P)
				0.0137	0.1852	(BC)
				0.0143	0.1843	(BCa)
Off-farm income	0.2279	0.0024	0.0704	0.1048	0.3792	(P)
				0.1066	0.3823	(BC)
				0.1053	0.3808	(BCa)
Total indirect effects	0.2929	0.0021	0.0828	0.1463	0.4678	(P)
				0.1497	0.4734	(BC)
				0.1484	0.4703	(BCa)

P percentile bootstrapped, *BC* bias corrected, and *BCa* bias corrected and accelerated 95% confidence intervals. Controls include individual characteristics (including age, age squared, years of schooling), household size and provincial dummies (Gansu as the reference province)

Table 9 Mediation of the effect of SU on happiness (using 5000 bootstrap samples)

Mediators	Observed		Bootstrap	95% Confidence intervals		
	Coef.	Bias	SE	Lower	Upper	
Farm income	0.0649	0.0004	0.0491	− 0.0222	0.1707	(P)
				0.0163	0.1793	(BC)
				0.0167	0.1782	(BCa)
Off-farm income	0.2365	0.0025	0.0722	0.1122	0.3934	(P)
				0.1178	0.4038	(BC)
				0.1163	0.4017	(BCa)
Total indirect effects	0.3014	0.0029	0.0832	0.1510	0.4753	(P)
				0.1531	0.4790	(BC)
				0.1521	0.4773	(BCa)

P percentile bootstrapped, *BC* bias corrected, *BCa* bias corrected and accelerated 95% confidence intervals. Controls include individual characteristics (including age, age squared, years of schooling), household size and provincial dummies (Gansu as the reference province)

One major finding is that SU is associated with increased SWB irrespective of whether the dependent variable is life satisfaction or happiness. Such effects are also likely to be larger at the median and upper tails of the SWB distribution. More important, our IV estimation confirms the significant and negative relation between SU and SWB. We also show that SU intensity—in particular, SU in excess of 3 h per day—undermines individual SWB. Interestingly, we confirm that SU–SWB is partially mediated by both farm income and off-farm income, suggesting that SU positively boosts farmers' SWB via increasing both farm income and off-farm income. Our finding is supported by Sekabira and Qaim [38], who show that the use of mobile phones boosts household income in rural Uganda.

5.2 Policy implications

The Chinese government has recently launched its strategy "Internet plus Agriculture" to facilitate the modernization of China's agriculture and especially to revitalize rural agriculture. This strategy aims to apply internet technology to improve the efficiency of the agricultural sector such as the trade of agricultural products [57]. Such a strategy is important as the structure of the agricultural system in China is characterized as "small-sized" and "highly scattered" family-based farms that focus predominantly on the production stage and less on other value chain services such as the processing and trade of agricultural products [57]. In the agricultural markets, farmers are at a competitive disadvantage due primarily to high production costs, low-profit margins, and problems with pollution and food safety [57]. The "Internet plus Agriculture" strategy aims to foster the integration, transformation, and upgrading of the rural economy. Our results emphasize the importance of the "Internet plus Agriculture" in connecting farmers to the modern economic systems via Internet technologies to increase farmers' income, lift them out of poverty and improve China's rural economy. Specifically, our results, highlight the mediation of farm income on the SU–SWB relation, which suggests that the local government should invest in Internet infrastructure to promote agricultural production activities and develop specific rural services (e.g. high-precision technology of pest prevention and control, data sharing on agricultural production, three-tier service facility system comprised of county service centers, township service stations and village service sites) to facilitate farmers better access to fast, real-time, and reliable information of agricultural production and market networks, thereby enhancing farmers' agricultural productivity and efficiency, and local and international sales of high-quality agricultural products. Considering the importance of off-farm income in the SU–SWB link, local governments should take advantage of mobile ICTs to provide more opportunities for rural entrepreneurship and innovation, in particular to motivate young farmers to actively engage in rural e-business ventures.

As highlighted by Sarwar and Soomro [59], it is of great importance to further the understanding of the positive and negative impacts of SU on social and economic development. Of course, possible interventions that avoid negative consequences of SU intensity should steer rural netizens to see mobile Internet use as a means for positively impacting their quality of life. Although smartphones have greatly improved people's modern life by reducing the cost of information gathering, facilitating interpersonal relationships, enriching entertainment choices, and boosting the effectiveness of online consumption, they are as capable of making close people distant as of bringing distant people closer and can thus seriously undermine our quality of life.

5.3 Limitations and future research directions

This study is, however, subject to several limitations. First, it is a cross-section study. Therefore, it is difficult to rule out all possibilities of endogeneity issues in the SU–SWB relation. Although our analysis tackles the endogeneity associated with SU, addressing the endogeneity of SU *intensity* is, in the absence of viable instruments, impossible. Second, our cross-sectional analysis prevents exploration of the dynamic relationship between SU and SWB. Third, although our analytic sample encompasses three provinces with different geographical and economic conditions, our data are not nationally representative. Finally, due to data availability, it is difficult for us to take a detailed look at all possible mechanisms through which SU operates on individuals' SWB. We have focused on important role of farm income and off-farm income. Thus, more research is needed to explore the causal relation between SU and SWB in rural China. Additionally, given that the SU-SWB associations in rural China will change over time as the mobile Internet becomes more prevalent and rural netizens become more experienced, more detailed, longitudinal and nationally representative data on SU and SWB in China is needed. It is also important to explore the causality in the nexus between SU intensity and SWB and other underlying pathways through which SU works on SWB in rural China, such as through enhance communications or social networks [59].

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Data availability The datasets during and/or analysed during the current study are available from the corresponding author on reasonable request.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Table 10.

Table 10 OLS estimates for smartphone use and SWB

	Life satisfaction (1)	Happiness (2)
Smartphone use	0.438**	0.146
	(0.197)	(0.191)
Age	−0.071	−0.079
	(0.050)	(0.049)
Age squared	0.000	0.001
	(0.001)	(0.001)
HH male	−0.371	−0.412*
	(0.230)	(0.220)
HH years of schooling	−0.013	−0.020
	(0.033)	(0.031)
Log (household income)	0.810***	0.927***
	(0.165)	(0.164)
Household size	0.034	0.024
	(0.056)	(0.053)
N	493	493
Village dummies	Yes	Yes
Adj. R^2	0.290	0.285

The dependent variables are 10-point-scale measure of life satisfaction and happiness (1 = very unsatisfied/unhappy to 10 = very satisfied/happy). Controls include smartphone use participation (1 = yes, 0 = no), individual characteristics (including age, age squared, years of schooling), household size and translog household total income, and village dummies (Yujing as the reference village). Robust standard errors are in parentheses

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

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