Article

Not peer-reviewed version

Impact of Internet Use on Health Status in China: Evidence Based on A national Longitudinal Survey Data

Ma Xinxin *

Posted Date: 2 August 2024

doi: 10.20944/preprints202408.0114.v1

Keywords: Internet use; Health status; Self-rated health; Mental health; Digital divide; China

 doi:10.20944/preprints202408.0114.v1

Article

Impact of Internet Use on Health Status in China: Evidence Based on A national Longitudinal Survey Data

Xinxin Ma

Faculty of Economics, Hosei University, 4342 Machita-shi Aiharamachi, Tokyo, 194-0298, Japan; xxma@hosei.ac.jp; Tel.: +81-42-783-2592

Abstract: Previous studies have examined the impact of Internet use on health in China, but they have not adequately addressed the issue of reverse causality or conducted a detailed analysis of health status. This study uses three waves of longitudinal data from the China Family Panel Studies conducted in 2014, 2016, and 2018 to investigate the association between Internet use and health status in China, aiming to address these gaps. The results indicate that Internet use may improve health status, including self-rated health, mental health, and outpatient visits. These effects vary by gender and age group: the positive effect of Internet use on health outcomes is more pronounced for women, and for middle-aged and older generations, compared to men and younger generations. These findings provide new evidence of the beneficial impact of Internet use on health outcomes in China, suggesting that policies promoting Internet utilization could enhance individuals' health status, particularly among women and middle-aged and older populations.

Keywords: internet use; health status; self-rated health; mental health; digital divide; China

1. Introduction

According to data from the China Network Internet Information Center (CNNIC), the number of internet users in China reached 904 million in April 2020 [1], making China the country with the largest number of internet users worldwide. Correspondingly, an increasing number of studies have examined the impact of internet use on society, including employment [2,3], income [4], happiness or life satisfaction [5,6], and health status [7–12] in many countries, including China.

Regarding the impact of internet use on individuals' health status, the empirical results are mixed. Several studies suggest that internet use improves health status by enhancing the utilization of healthcare services [13,14], obtaining more medical information [15], and increasing connections with others, thereby boosting social capital and social participation [16,17]. On the contrary, some studies find that internet use has a negative effect on health status. For example, excessive internet use can lead to mental health disorders, and internet use can reduce face-to-face communication, which significantly affects mental health [18,19]. Thus, the overall effect of internet use on health is not clear based on current economic theory and empirical evidence; it should be evaluated through more empirical studies.

This study examines the association between internet use and five types of health indicators using three-wave longitudinal data from the China Family Panel Studies (CFPS) conducted in 2014, 2016, and 2018. The results indicate that internet use is positively associated with health status (self-rated health, mental health, and outpatient care), and these effects differ by gender and age group. The findings provide new evidence of the positive effect of internet use on health outcomes in China, a large developing country with a large population and rapid internet development. The empirical results suggest that policies promoting internet utilization are generally expected to improve individuals' health status, particularly among women and middle-aged and older populations.

This study significantly contributes to the related literature in three ways. First, although some studies have used data from the CFPS and reported that internet use positively affects self-rated health (SRH), they all performed cross-sectional analyses [11,20–23]. Consequently, econometric

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 August 2024 doi:10.20944/preprints202408.0114.v1

problems such as the initial value effect (i.e., the effect of a variable's initial value on its current value) and reverse causality may still be present in their results. Using three waves of longitudinal survey data from the China Family Panel Studies (CFPS), this study examines the association between Internet use and health status, employing a lagged variable of Internet use to address the issue of reverse causality. Additionally, the study incorporates a lagged variable of health status to control for the initial value of health status. This approach allows the study to provide more robust evidence on the relationship between Internet use and health status.

Second, unlike previous studies that concentrated on one type of health status (most commonly SRH), this study constructs a set of indicators of health outcomes, including SRH, mental health, chronic diseases diagnosed by a doctor, outpatient visits, and inpatient visits. This comprehensive set of indicators provides rich evidence on the issue. Specifically, SRH and mental health are used as indicators of subjective health outcomes, while chronic disease, outpatient and inpatient care are used as indicators of objective health outcomes. The results thus enrich the understanding of health outcomes.

Third, although some studies have reported that the impact of internet use differs by age and urban/rural area group [23], no study has analyzed these differences by gender. This study is the first to compare the differences in the effects of internet use on health by gender, as well as differences between age and urban/rural area groups in China.

The remainder of this paper is organized as follows. Section 2 reviews related literature, and develops four hypotheses for the empirical study. Section 3 introduces the methodology, model, data, and variable settings. Section 4 reports the econometric analysis results. Section 5 discusses and explains the empirical results. Finally, Section 6 concludes the study.

2. Literature Review and Hypotheses Development

This study develops four hypotheses to explore the relationship between internet use and health outcomes in China.

In general, internet use has both positive and negative effects. The positive effects are as follows:

(i) The utilization of healthcare services significantly affects health outcomes [13,14]. According to medical care demand theory, the utilization of healthcare services is determined by the benefits and costs of medical care. Besides direct costs (e.g., medical expenses), indirect costs may also affect the utilization of healthcare services. Internet use can reduce healthcare indirect costs such as travel costs, arrangement costs, and waiting time to visit a doctor in a clinic/hospital, which may increase the efficiency of healthcare (indirect cost reduction effect).

(ii) Some empirical studies have reported that there is a problem of information asymmetry in the medical care market [15,24], which can reduce the efficiency of healthcare service utilization. Internet use can address this problem by reducing the medical information search cost, encouraging individuals to acquire more healthcare knowledge, and improving their health outcomes (obtaining medical information and knowledge effect).

(iii) Based on the social capital hypothesis, internet use can increase connections with others, social capital, and social participation [16,17]. It has been reported that increased social capital and social participation can improve health [17,25–27] (increasing social capital and social participation effect).

On the other hand, internet use also has negative effects on health:

(iv) Longer hours of internet use and addictive behavior can affect sleep and mental health, especially in the younger generation [7] (problematic use effect).

(v) Internet use may reduce face-to-face communication and crowd out several dimensions of social capital [28], leading to feelings of loneliness [19] and increasing the probability of developing mental health disorders [29] (decreasing social capital effect).

Although internet use has both positive and negative effects on health status, we predict that the positive effects outweigh the negative effects. Hence, Hypothesis 1 (H1) is proposed as follows:

H1: Internet use positively affects health status.

 doi:10.20944/preprints202408.0114.v1

The gender digital gap in internet access in developed countries emerged in the early stages of ICT development [30] but has reduced with the increasing diffusion of digital technologies [31]. In developing countries, women have a significantly lower likelihood of internet access than men, and this gender disparity in internet use can exacerbate the overall socio-economic gender gap [7,32]. China, a developing country, also faces a gender digital divide [33]. The 45th Statistical Report on the Development of the Internet in China reveals that the number of internet users in China reached 904 million in April 2020, with women accounting for 48.1% (up from 30.4% in 2000) [1]. These statistics suggest the existence of a gender disparity in internet access in China. Since there are fewer female Internet users compared to male users, Internet usage may provide more health benefits for women who are users than for non-users, and this effect may be greater for women than for men. Additionally, compared to men, women tend to place a higher value on social connections with others; therefore, Internet use may significantly enhance social connections among women, which in turn could improve their health status more than it does for men. Based on this, Hypothesis 2 (H2) is proposed as follows:

H2: The impact of internet use on health status is greater for women than for men.

Regarding the difference in the impact of Internet use between older and younger generations, several studies have explored how Internet use improves the health status of older adults [34]. Potential pathways for these effects are considered as follows: First, Internet use may enhance connections between older individuals and their children, relatives, or others. This increased social network or social connection may boost their social capital and improve their health status [35]. Second, older people may obtain more medical information through Internet use, which could improve their health behaviors, such as reducing smoking and drinking and increasing exercise. Third, with advancements in online appointment systems, Internet use may improve the efficiency of utilizing medical care services. As the utilization of medical care services (e.g., outpatient, inpatient) is generally higher among older generations than younger generations, Internet use may significantly enhance the efficiency of medical care service utilization for older generations more than for younger generations. Additionally, several studies have found that excessive Internet use significantly worsens mental health among younger generations [7,36–38]. Therefore, this study predicts Hypothesis 3 (H3) as follows:

H3: The effect of Internet use on improving health status is greater for middle-aged and older generations than for younger generation.

In China, the inclusive growth of the economy is severely restricted by income inequality, with one significant manifestation being the substantial income gap between urban and rural residents [39]. Lower income levels among rural residents contribute to poorer health status compared to their urban counterparts. Additionally, there is a digital divide between rural and urban areas [40–43]. Internet infrastructure varies significantly between these areas, with urban areas having higher internet penetration rates. According to the 45th Statistical Report on the Development of the Internet in China, the number of internet users in China reached 989 million in June 2020, including 680 million urban residents and 309 million rural residents; the internet penetration rates were 76.4% for urban residents and 52.3% for rural residents [1]. Both the number of internet users and the proportion of individuals using the internet are lower among rural residents. Therefore, the positive impact of Internet use on health status may be greater for rural residents than for urban residents. However, as the average education level is lower for rural residents compared to urban residents, their internet use skills may also be lower [43].

Given that internet accessibility and internet use skills are lower among rural residents than urban residents, the impact of Internet use on improving health status may be smaller for rural residents than for their urban counterparts. However, compared to urban residents, rural residents

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 August 2024 doi:10.20944/preprints202408.0114.v1

have less access to medical information and lower levels of healthcare services. Therefore, Internet use may significantly address information asymmetry, which could lead to greater improvements in health status for rural residents than for urban residents.

Since these opposing effects may cancel each other out, the difference in the impact of Internet use on health status between urban and rural residents may be small. Hence, Hypothesis 4 (H4) is proposed as follows:

H4: The difference in the impact of internet use on health status between urban and rural residents is small.

3. Empirical Strategy

3.1. Model

As the benchmark, this study uses a logistic regression model to estimate the association between Internet use and health outcomes, along with a set of covariates:

$$H_i = a + \beta INT_i + \sum_n \delta_n X_{ni} + \varepsilon_i, \qquad (1)$$

where i and n denote the individual and types of covariates.H presents a set of indices of health status (e.g., SRH, mental health, chronic disease, inpatient care or outpatient care), INT presents the Internet use variable. X is covariate variable, a is constant term and ε is an error term. β and δ_n are estimated coefficients of Internet use variable and covariates. The results of β are noticed in this study.

There may exist the reverse causality problem in Eq. (1). For example, Internet use status at time *t* might be affected by Internet use status at time $t-1$ (e.g., an individual who used Internet in time $t-1$ is likely to use Internet at time *t*). This study uses the Internet use status at time $t-1$ to mitigate the reverse causality problem by allowing a one-wave (that is, two-year) lag from Internet use to health.

There also may exist the initial value problem [44,45]in Eq. (1). For instance, health status at time *t* might be affected by health status at time $t-1$. To deal with this problem, this study uses a dynamic model that included health at time $t-1$ as an explanatory variable. It also uses the Internet use status at time $t-1$ to mitigate the reverse causality problem by allowing a one-wave (that is, two-year) lag from Internet use to health.

Overall, this study uses the following dynamic logistic regression model, expressed by Eq. (2).

$$H_{it} = a + \rho H_{it-1} + \beta INT_{it-1} + \sum_n \delta_n X_{nit-1} + u_{it}, \qquad (2)$$

where t and $t-1$ denote a set of survey years (2014 and 2016) or (2016 and 2018), and u is an error term.

The model is applied not only to the entire sample but also to specific groups based on sex (women and men), age (16–24, 25–44, 45–59, and 60 or above), and area of residence (urban and rural) to examine differences in the impact of Internet use among these various groups.

3.2. Data

This study uses data from the China Family Panel Studies (CFPS), a nationwide longitudinal survey conducted by Peking University in representative regions of China in 2014, 2016, and 2018. The study employs the nationwide weight (fswt_nat in CFPS 2010). The CFPS is designed to collect longitudinal data at the individual, family, and community levels in contemporary China.

The sample for the 2010 CFPS baseline survey was drawn using a multi-stage probability sampling method with implicit stratification. In the 2010 baseline survey, the CFPS successfully interviewed approximately 15,000 families and nearly 30,000 individuals within these families, with an approximate response rate of 79%. Respondents were tracked through annual follow-up surveys.

The CFPS covered 25 provinces and municipalities in 2010 and expanded to 31 provinces in subsequent surveys. This study utilizes the latest three waves (2014, 2016, and 2018) of the CFPS, which included detailed survey items on internet use.

The CFPS provides extensive individual- and household-level information, including health indices, demographic characteristics, family structure, household income, health behavior, and enrollment in social insurance, all of which are used in this study.

The sample sizes for the CFPS waves in 2014, 2016, and 2018 were 37,147, 36,892, and 37,354, respectively. This study focuses on individuals aged 16 years or older in the baseline survey who participated in at least one of the two follow-up surveys. After excluding respondents with missing key variables used in the statistical analysis, the total number of samples used in this study is 60,077 (20,024 from 2014, 20,026 from 2016, and 20,027 from 2018). The number of samples used in the regression analyses varies slightly depending on the model.

3.3. Variable Setting

(1) Health Status Indicators

The key dependent variables in this study are five indices of health status:

(i)Self-Rated Health (SRH)

(ii)Mental Health, including total mental health disorder (TMH) and six specific types of mental health issues (MH1–6)

(iii)Chronic diseases

(iv)Outpatient care

(v)Inpatient care

All of these variables are binary. This study selects common or similar questions related to mental health from the three survey waves. The SRH, TMH, and inpatient care indices have been used in previous literature [12,46]. The specific mental health indicators (MH1–6), chronic disease, and outpatient care are used in this study for the first time, providing new evidence on these issues. Higher values indicate poorer health status for all health outcome indices. The indicators for each health outcome are as follows:

- *Self-Rated Health (SRH)*

  Based on a five-point scale question on self-rated health (1=excellent, 2=good, 3=normal, 4= poor, 5=very poor), the binary SRH variable is constructed as 0 = excellent or good and 1=otherwise.
- *Mental Health Indicators*

  For TMH and MH1–6, answers to questions on mental health are categorized. The questions differ slightly each year, but the common six items selected are:
- (i) I find nothing exciting (MH1)

  (ii) I feel nervous (MH2)

  (iii) I cannot concentrate on things (MH3)

  (iv) I feel depressed (MH4)

  (v) I find it difficult to do anything (MH5)

  (vi) I feel that I cannot continue with my life (MH6)

Based on a five-option scale for responses ("weekly 5–7 days = 4, weekly 3–4 days = 3, weekly 1–2 days = 2, weekly less than 1 day or never = 1"), scale variables for MH1–6 are constructed. The total score for MH1–6 (TMH) ranges from 6 to 24. TMH and MH1–6 is based on the original CFPS questionnaire, with MH1–6 used for the first time in this study. Higher values indicate a higher probability of developing a mental health disorder.

- *Chronic Diseases*

A binary variable for chronic disease is constructed, with 1 assigned to individuals who reported having one or more diseases diagnosed by doctors and 0 otherwise.

- *Outpatient and Inpatient Care*

Binary variables are constructed for outpatient and inpatient care, with 1 assigned to individuals who reported experiencing outpatient or inpatient care in the survey year and 0 otherwise.

(2) Internet Use Variable

The key independent variable is the internet usage dummy variable. Based on the question, "Did you use the internet in the past year?", internet usage is coded as 1 for "used the internet" and 0 for "did not use the internet."

(3) Covariates

Referring to previous studies on health outcomes, this study considers the following covariates, all of which are likely to affect health outcomes and are available from the CFPS:

- *Demographic Factors*

Numerous studies have reported that age, sex, years of education, and ethnicity affect health status [11,12,20,36,47,48]. Additionally, in China, Communist Party of China members often have higher socio-economic status and more social capital (e.g., party membership) [49,50], which may influence health outcomes. Furthermore, the urban-rural household registration system *(hukou)* creates significant disparities between urban and rural residents, such as differences in income [39] and social security systems, including public health insurance [51]. Therefore, party membership and urban-rural dummy variables are included in the analysis.

- *Family Factors*

Some empirical studies find that family factors, such as having a spouse and the number of family members, affect health status [52]. Thus, these factors are controlled in the analysis.

- Income Factor

Numerous studies have found that health outcomes differ by income group, and household income/wealth significantly affects an individual's health status [53]. This study uses per capita household income to control for the influence of income on health status.

- *Health Behavior*

Based on health demand theory, some studies investigate the impact of health behaviors on health status and find that smoking and drinking affect health outcomes [54]. This study includes variables for smoking (1=smoking, 0=non-smoking), drinking (1=drinking daily, 0=otherwise), and the number of weekly exercise sessions in the analysis.

- *Institutional Factors*

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 August 2024 doi:10.20944/preprints202408.0114.v1

Numerous empirical studies report that institutional factors, especially public medical insurance, significantly affect health outcomes [51,55]. The analysis includes dummy variables for enrollment in pension and medical insurance (1 = enrolled, 0 = otherwise).

- *Other Factors*

Regional disparities in economic development, living conditions, lifestyle, or culture may also affect health outcomes [56]. This study includes three regional dummy variables (east, central, and west) to control for regional disparities. Additionally, dummy variables for the survey years (2014, 2016, and 2018) are used to control for economic cycles and trends in health status over time.

4. Descriptive Statistics Results

Table 1 summarizes the key features of the study samples used in the statistical analysis. The proportion of individuals who reported having used the Internet in the past year was 40.4% in China from 2014 to 2018. There are notable differences in individual attributes, family structure, household income, and enrollment in social insurance between Internet users and non-users. For example, Internet users tend to have more years of schooling, are older, have a lower proportion of women, and have higher household income compared to non-users. Therefore, these factors should be controlled in the analysis.

Table 1. Differences in individual characteristics between Internet users and non-users.

	(a)Total	(b) User	(c) Non-user	Difference	
				(b) – (c)	*t*-test (*p*-value)
Internet use	0.404				
Demographic factors					
Education (years)	7.731	10.787	5.625	5.162	0.000
Age (years)	46.517	36.614	53.804	-17.19	0.000
Women	0.496	0.478	0.514	-0.036	0.000
Ethnicity (Han)	0.96	0.94	0.977	-0.037	0.000
Party membership	0.059	0.071	0.05	0.021	0.000
Urban	0.475	0.607	0.391	0.216	0.000
Family factors					
Having a spouse	0.89	0.784	0.973	-0.189	0.000
Number of family members	4.324	4.293	4.327	-0.034	0.042
Household income (yuan)	16552	22476	12773	9703	0.000
Health behavior					
Smoking	0.28	0.284	0.295	-0.011	0.007
Drinking	0.152	0.143	0.168	-0.025	0.000
Exercise (times)	2.209	2.331	2.148	0.183	0.000
Social insurance					
Pension	0.464	0.503	0.441	0.062	0.000

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 August 2024 doi:10.20944/preprints202408.0114.v1

Medical insurance	0.918	0.898	0.932	-0.034	0.000
Regions					
East	0.411	0.445	0.396	0.049	0.000
Central	0.297	0.304	0.294	0.010	0.090
West	0.292	0.251	0.31	-0.060	0.000
Survey years					
y2014	0.333	0.233	0.377	-0.144	0.000
y2016	0.333	0.339	0.333	0.006	0.090
y2018	0.334	0.428	0.29	0.138	0.000
N	60077	24271	35806		

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note Mean values are summarized. The SD values of age, years of education, number of family members, and per capita household income are shown in paratheses.

Table 2 presents the unadjusted associations between Internet use in 2016 and health outcomes in 2018, comparing health outcomes between Internet users and non-users using the entire sample. High values indicate poorer health outcomes. The results show that Internet use is positively associated with self-rated health (SRH), total mental health disorder (TMH), mental health indicators MH3-6, chronic disease, outpatient visits, and inpatient care. However, it should be noted that these comparisons are not adjusted for covariates and do not account for potential biases related to cross-sectional analysis.

Table 2. Unadjusted association between Internet use in 2016 and health outcomes in 2018.

Health status (2018)	User (2016) (a)	Non-user (2016) (b)	Difference (a) – (b)	*t*-test *p*-value	*N*
Self-rated health (SRH: 1–5)	2.756	3.247	-0.491	0.000	37870
Total Mental health (MHT: 6-24)	8.182	8.604	-0.422	0.000	37434
Mental health (MH1: 1–4)	1.435	1.381	0.053	0.000	37453
Mental health (MH2: 1–4)	1.268	1.229	0.039	0.000	37460
Mental health (MH3: 1–4)	1.695	1.816	-0.121	0.000	37467
Mental health (MH4: 1–4)	1.101	1.163	-0.062	0.000	37458
Mental health (MH5: 1–4)	1.564	1.79	-0.225	0.000	37454
Mental health (MH6: 1–4)	1.118	1.226	-0.108	0.000	37458

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The higher the score, the worse the health status. MH1: I find nothing exciting; MH1: I find nothing exciting; MH3: I cannot concentrate on things; MH4: I feel depressed; MH5: I find it difficult to do anything; MH6: I feel that I cannot continue with my life. The covariates were not controlled.

4. Econometric Analysis Results

4.1. Baseline Results

The basic results using the dynamic LV logistic regression models are summarized in Table 3, which presents a panel data analysis using the lagged variable (LV) model, controlling for initial health status in the first wave and Internet use in the prior survey year. The table reports the odds ratios (ORs) of health status, along with 95% confidence intervals (CIs), in response to Internet use.

The results show that Internet use has negative and significant associations ($p < 0.05$) with poor self-rated health (SRH) (OR: 0.84, 95% CI: 0.78–0.91), mental health indicator MH4 (OR: 0.65, 95% CI: 0.51–0.83), mental health indicator MH5 (OR: 0.83, 95% CI: 0.75–0.92), mental health indicator MH6 (OR: 0.62, 95% CI: 0.49–0.79), and inpatient care (OR: 0.90, 95% CI: 0.80–1.00). The results suggest that Internet use may reduce the probability of experiencing poor health status, supporting Hypothesis 1.

Table 3. Baseline results.

	OR	95% CI	*N*
Self-rated health (SRH)	0.843***	(0.78, 0.91)	33238
Total mental health (TMH)	0.939	(0.84, 1.05)	33155
MH1	0.906	(0.79, 1.04)	33204
MH2	1.000	(0.85, 1.18)	33228
MH3	1.141***	(1.05, 1.24)	33229
MH4	0.648***	(0.51, 0.83)	33211
MH5	0.832***	(0.75, 0.92)	33219
MH6	0.624***	(0.49, 0.79)	33214
Disease (0–1)	1.0423	(0.95, 1.15)	33242
Outpatient (0–1)	0.979	(0.90, 1.06)	33242
Inpatient (0–1)	0.900**	(0.80, 1.00)	33242

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in time t-1, education, age, age squared term, sex, ethnicity, party, urban, household income, number of family members, marital status, health behavior, social insurance, region (east, central, and west regions), and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. ***: p<0.01; **: p<0.05; *: p<0.1.

This study also employs results from other cross-sectional data analysis methods. The results are summarized in Appendix Tables A1. The significance and magnitude of the effect are smaller in the panel data analysis methods (a dynamic LV model in Table 3) compared to the cross-sectional analysis (Appendix Table A1). This suggests that the initial value problem and reverse causality issue may significantly affect the impact of Internet use on health status and should be addressed in the analysis. Consequently, there may be bias in the existing literature that relied solely on cross-sectional data.

4.2. Results by Heterogenous Group

Tables 4–6 summarize the results obtained from separate estimations by gender, age, and area group using the dynamic LV model. Table 4 shows that Internet use has significant negative associations with poor self-rated health (SRH), as well as mental health disorders MH3 and MH4, and modest negative associations with total mental health (TMH) and MH6 ($p < 0.1$) for men. For women, Internet use significantly negatively associates with poor SRH and mental health disorders MH4–6. The results indicate that Internet use positively impacts health status for both men and women, with the effect being modestly greater for women than men. These results support Hypothesis 2.

Table 5 compares the association between Internet use and health by age group. The most notable finding is that the positive effect of Internet use on self-rated health (SRH) and mental health is insignificant for the younger generation (aged 16–24 years) compared to middle-aged and older generations (aged 45–59 and 60 and over). Additionally, Internet use significantly increases the probability of outpatient visits among younger generations (OR: 2.06, $p < 0.01$). The results suggest that the impact of Internet use on improving health status is greater for middle-aged and older generations than for the younger generation. These findings support Hypothesis 3.

Table 6 compares the association between Internet use and health in urban and rural area groups. The results show that Internet use has significantly negative associations with poor SRH for both urban and rural area groups, significantly negative associations with mental health disorders of MH5 and MH6, and modestly negative associations with mental health disorders of MH4 ($p < 0.1$) for the urban group. For the rural group, Internet use has significantly negative associations with mental health disorders of MH4 and MH6, and significantly negative associations with outpatient visits for the urban group and inpatient visits for the rural group. In sum, Internet use has a positive effect on improving the health status of both urban and rural groups, and the differences in the impact of Internet use on health status between urban and rural residents are small. These results support Hypothesis 4.

This study also employed estimations using the interaction term of Internet use and each group dummy variable (see Appendix Tables A2–A4). The results confirmed the above findings, supporting Hypotheses 2, 3, and 4 again.

Table 4. Results by gender.

	Men		Women	
	OR	95% CI	OR	95% CI
SRH	0.833***	(0.75, 0.93)	0.849***	(0.76, 0.95)
TMH	0.874*	(0.74, 1.03)	0.985	(0.85, 1.14)
MH1	0.859	(0.69, 1.06)	0.939	(0.78, 1.13)
MH2	0.984	(0.77, 1.25)	1.008	(0.80, 1.27)
MH3	1.222***	(1.07, 1.39)	1.061	(0.95, 1.19)
MH4	0.662**	(0.46, 0.96)	0.649**	(0.47, 0.90)
MH5	0.913	(0.79, 1.06)	0.749***	(0.65, 0.87)
MH6	0.707*	(0.50, 1.00)	0.579***	(0.42, 0.80)
Disease (0–1)	1.013	(0.88, 1.16)	1.062	(0.93, 1.21)
Outpatient (0–1)	0.967	(0.85, 1.09)	0.993	(0.89, 1.11)
Inpatient (0–1)	0.889	(0.76, 1.04)	0.919	(0.79, 1.07)

Source Calculated based on the data from CFPS of 2014, 2016, and 2018.Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in t-1 time, education, age, age squared term, ethnicity, party, urban, household income, number of family members, marital status, health behavior, social insurance, region (east, central, and west regions), and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. ***: p<0.01; **: p<0.05; *: p<0.1.

Table 5. Results by age.

	Aged 16-24		Aged 25-44		Aged45-59		Aged 60 or above	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
SRH	1.151	(0.67, 1.98)	0.900*	(0.79, 1.02)	0.842***	(0.74, 0.95)	0.672***	(0.54, 0.84)
TMH	1.732	(0.84, 3.59)	0.875	(0.73, 1.05)	0.91	(0.77, 1.08)	0.701*	(0.47, 1.03)
MH1	1.069	(0.44, 2.57)	0.84	(0.66, 1.05)	0.957	(0.77, 1.18)	0.676	(0.42, 1.10)
MH2	1.192	(0.47, 2.97)	0.905	(0.68, 1.20)	1.005	(0.78, 1.29)	0.907	(0.50, 1.64)
MH3	1.328	(0.81, 2.18)	1.134*	(0.98, 1.30)	1.172**	(1.03, 1.34)	0.773*	(0.59, 1.01)

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 August 2024 doi:10.20944/preprints202408.0114.v1

MH4	0.271*	(0.06, 1.15)	0.577***	(0.38, 0.87)	0.730*	(0.51, 1.04)	0.942	(0.47, 1.91)
MH5	1.623	(0.75, 3.50)	0.856*	(0.72, 1.02)	0.825**	(0.70, 0.97)	0.722**	(0.53, 0.98)
MH6	0.706	(0.19, 2.58)	0.630**	(0.43, 0.92)	0.608***	(0.42, 0.88)	0.49	(0.19, 1.22)
Disease (0–1)	0.962	(0.47, 1.97)	1.215*	(1.01, 1.46)	1.023	(0.89, 1.78)	0.937	(0.75, 1.17)
Outpatient (0–1)	2.055***	(1.17, 3.59)	0.978	(0.82, 1.12)	0.955	(0.84, 1.87)	0.832	(0.65, 1.05)
Inpatient (0–1)	0.903	(0.49, 1.65)	0.884	(0.73, 1.08)	0.96	(0.87, 1.13)	0.966	(0.75, 1.24)

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in t-1 time, education, sex, ethnicity, party, urban, household income, number of family members, marital status, health behavior, social insurance, region (east, central, and west regions), and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Table 6. Results by urban and rural residents.

	Urban		Rural	
	OR	95% CI	OR	95% CI
SRH	0.824***	(0.74, 0.91)	0.854**	(0.76, 0.96)
TMH	0.904	(0.77, 1.05)	0.973	(0.83, 1.35)
MH1	0.862	(0.71, 1.05)	0.941	(0.77, 1.15)
MH2	0.91	(0.71, 1.16)	1.067	(0.84, 1.35)
MH3	0.114*	(0.99, 1.25)	1.199***	(1.05, 1.37)
MH4	0.704*	(0.49, 1.019	0.609***	(0.43, 0.86)
MH5	0.790***	(0.68, 0.92)	0.915	(0.79, 1.06)
MH6	0.617***	(0.44, 0.87)	0.610***	(0.44, 0.87)
Disease (0–1)	0.995	(0.88, 1.24)	1.118	(0.96, 1.30)
Outpatient (0–1)	0.893**	(0.80, 1.00)	1.093	(0.96, 1.24)
Inpatient (0–1)	0.952	(0.83, 1.10)	0.829**	(0.67, 0.99)

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in t-1 time, education, age, age squared term, sex, ethnicity, party, household income, number of family members, marital status, health behavior, social insurance, region (east, central, and west regions) and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. ***: $p<0.01$; **: $p<0.05$; *: $p<0.1$.

Discussions

This study examined the effects of Internet use on health status in China from 2014 to 2018. The empirical analysis, based on three waves of longitudinal data, indicated that Internet use has significant positive associations with SRH. The results for SRH are generally in line with the positive findings from previous studies in China using cross-sectional data analysis methods [20,22,23] and a study that only used two waves of longitudinal data [11], which did not fully control for statistical biases.

Regarding the association between Internet use and other health outcomes (i.e., chronic disease, MH1~6, outpatient visit), which were estimated in this study for the first time for China, the results indicate that Internet use may reduce the probability of developing a mental health disorder. These findings contribute to the literature on the association between Internet use and health outcomes from multiple perspectives. In 2017, it was reported that 792 million people lived with a mental health disorder, representing 10.7% of the global population, which is slightly more than one in ten people worldwide [57]. The World Health Organization (WHO) reported that 54 million people in China suffered from depression and about 41 million from anxiety disorders [58], and the proportion of people with mental health disorders in China was more than 12% of the global total. In addition to increasing public health care expenditure on the treatment of mental health disorders, the results suggest that policies promoting the digital economy and expanding Internet penetration may contribute to improving mental health status.

The empirical results indicate that the positive effect of Internet use is modestly more significant for women than for men, suggesting that Internet use may significantly improve health status (especially mental health) to a greater extent for women. It is argued that a gender digital gap exists in Internet access that arose in developed countries in the early stages of ICT development [30,59]. According to data from the CNNIC, the proportion of Internet users in China was smaller for women than for men [1]. Thus, policies aimed at reducing the gender gap in Internet accessibility may contribute to improving women's health status more significantly in the future, thereby enhancing the nation’s overall well-being.

The results also indicate disparities in the effects of Internet use among age groups. The positive effect of Internet use on health outcomes is greater for middle-aged and older generations. This may be because the problem of addictive use (overuse) of the Internet is more serious among younger generations compared to other age generations, as teenagers have a weaker ability to control Internet addiction than adults. A systematic review study [7] reported a link between excessive social media use and negative health outcomes in youth worldwide. It is also argued that in China, Internet gaming addiction and prolonged smartphone use harm the mental health of adolescents [60,61]. Using data from the CFPS of 2016, this study calculated the frequency score of Internet use for entertainment based on an eight-scale question (everyday=7, never=0). The scores were 4.18 for the group aged 11-24, 2.40 for the group aged 25-49, and 0.42 for the group aged 50 and above, suggesting that the younger populations spend more time on Internet use for entertainment than the middle-aged and older populations do. Therefore, the Chinese government should consider policies to address the younger populations’ problematic use of the Internet.

In light of the results of this study, it is expected that policies promoting Internet development may improve the nation’s health status. To reduce digital divide problems, the Chinese government should consider policies for reducing problematic Internet use among teenagers, promoting Internet infrastructure expansion in rural areas, and reducing gender disparities and urban-rural gaps in Internet access and educational attainment. These policies are expected to bridge the digital divides between disadvantaged groups (e.g., women, rural residents, older generation) and advantaged groups (e.g., men, urban residents, younger generation), which may enhance sustainable societal development from a long-term perspective.

Conclusions

This study concludes that Internet use tends to improve health status across China, with the positive effects being greater for women, and middle-aged and older generations than for men and younger generations, based on three-wave longitudinal data from 2014 to 2018.

This study has several limitations. First, although we used a dynamic LV model to address the initial value problem and reverse causality issue, the endogeneity problem could not be fully addressed. Future research should explore using other econometric models (the Difference-in-Differences, Instrumental Variable methods, etc.) to investigate the causal association between Internet use and health status. Second, this study did not identify the channels through which Internet use affects health status, which should be investigated in more in-depth analyses. Third, as no policy reforms related to Internet use occurred during the period 2014–2018, this study could not examine the effect of Internet promotion policies on health outcomes. This presents another avenue for future research.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 2 August 2024 doi:10.20944/preprints202408.0114.v1

Despite these limitations, the current study, which leverages three waves of national longitudinal data, provides new insights into the association between Internet use and health outcomes from both nationwide and subgroup perspectives. The Chinese experience may also offer valuable lessons for other countries aiming to improve national health outcomes in the digital economy era worldwide.

Author Contributions: X. M. organized this research project, conceptualized and designed the study, collected the data, performed the analyses, prepared the original and final manuscript, and obtained research funding.

Ethics approval and consent to participate: The dataset that was used in this study, the China Family Panel Studies (CFPS) was conducted and managed by Peking University, and its study protocol was approved by the Ethical Review Committee of Peking University. Survey data were obtained from the CFPS with its permission from Peking University. Hence, the current study did not require further ethical approval and the need for written consent was waived by the committee.

Availability of data and materials: The dataset used in this study, the China Family Panel Studies (CFPS), was managed by Peking University, China. The datasets and materials constructed by the authors are available on request.

Competing interests: The author declares no competing interests.

Funding: This research was financially supported by a research fund from Japan Society for the Promotion Science (Grant number: 20H01512). The funding body had no role in the design of the study; the collection, analysis, and interpretation of the data; or in writing the manuscript.

Appendix A

Table A1. Results using cross-sectional data.

	(1) Pooling regression			(2) Pooling regression +covariates		
	Coef.	95% CI	*N*	Coef.	95% CI	*N*
SRH	-0.473***	(-0.49,0.45)	57895	0.024*	(-0.004,0.05)	50570
TMH	-0.469***	(-0.52, -0.42)	57793	0.126***	(0.06,0.20)	50486
MH1	-0.009***	(-0.02,0.004)	57852	0.054***	(0.04,0.07)	50533
MH2	-0.027***	(-0.04, -0.02)	57879	0.030***	(0.02,0.05)	50556
MH3	-0.068***	(-0.08, -0.05)	57887	0.052***	(0.03,0.07)	50557
MH4	-0.088***	(-0.10, -0.08)	57855	0.000***	(-0.01,0.01)	50540
MH5	-0.157***	(-0.18, -0.14)	57870	0.005***	(-0.02,0.02)	50549
MH6	-0.125***	(-0.13, -0.16)	57864	-0.015**	(-0.03,0.001)	50544

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The logistic regression model was used. Covariates including SHR or MH1-6, education, age, age squared term, sex, ethnicity, party, urban, household income, family number, married, health behavior, social insurance, region and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. ***: p<0.01; **: p<0.05; *: p<0.1.

Table A2. Differences in Internet use effect on health status by sex.

(1) Internet_t-1		(2) Female		(3) Internet_t-1×Female		
OR	95% CI	OR	95% CI	OR	95% CI	*N*

 doi:10.20944/preprints202408.0114.v1

SRH_t	0.901**	(0.81, 0.99)	1.216***	(1.12, 1.31)	0.884**	(0.78, 1.00)	32731
TMH_t	1.027	(0.89, 1.19)	1.517***	(1.36, 1.69)	0.953	(0.81, 1.12)	32696
MH1_t	0.978	(0.81, 1.18)	1.621***	(1.40, 1.88)	0.931	(0.75, 1.15)	32696
MH2_t	1.167	(0.94, 1.44)	1.244**	(1.05, 1.48)	0.836	(0.65, 1.07)	32720
MH3_t	1.390***	(1.24, 1.55)	1.971***	(1.80, 2.16)	0.697***	(0.61, 0.97)	32721
MH4_t	0.721*	(0.51, 1.01)	1.287**	(1.05, 1.58)	1.037	(0.69, 1.56)	32712
MH5_t	0.993	(0.87, 1.13)	1.296**	(1.18, 1.42)	0.760***	(0.64, 0.89)	32712
MH6_t	0.743*	(0.54, 1.02)	1.376***	(1.14, 1.66)	0.908	(0.62, 1.34)	32707
LS_t	1.1883	(0.92, 1.52)	1.066	(0.86, 1.31)	0.811	(0.59, 1.11)	33219

Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in time t-1, education, age, age squared term, ethnicity, party, urban, household income, number of family number, marital status, health behavior, social insurance, region (east, central, west regions) and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. Internet_t-1×Female represents the interaction term of Internet use in time t-1 and female dummy. ***: p<0.01; **: p<0.05; *: p<0.1.

Table A3. Differences in Internet use effect on health status between younger and middle-aged and older age groups.

	(1) Internet_t-1		(2) Age60+		(3) Internet_t-1×Age60+		
	OR	95% CI	OR	95% CI	OR	95% CI	*N*
SRH	0.630***	(0.58, 0.68)	1.330***	(1.23, 1.43)	1.155	(0.92, 1.44)	32731
TMH	0.869***	(0.78, 0.96)	1.077	(0.97, 1.12)	0.798	(0.54, 1.18)	33155
MH1	0.879*	(0.78, 1.00)	1.099	(0.96, 1.25)	0.758	(0.47, 1.23)	32696
MH2	0.943	(0.80, 1.10)	0.988	(0.85, 1.15)	0.894	(0.50, 1.61)	32720
MH3	0.974	(0.85, 1.06)	1.319***	(1.22, 1.43)	0.759**	(0.58, 0.99)	32721
MH4	0.548***	(0.43, 0.70)	1.036	(0.86, 1.25)	2.073	(1.01, 4.24)	32704
MH5	0.651***	(0.59, 0.72)	1.338***	(1.22, 1.46)	1.18	(0.86, 1.61)	32712
MH6	0.554***	(0.44, 0.70)	1.035	(0.88, 1.22)	1.096	(0.47, 2.75)	32707
LS	1.027	(0.85, 1.24)	0.584***	(0.47, 0.72)	2.130**	(1.04, 4.33)	33219

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in time t-1, education, sex, ethnicity, party, urban, household income, number of family members, marital status, health behavior, social insurance, region (east, central, west regions) and year dummy variables were estimated, but they were not expressed in the table. Internet_t-1×Age 60+ represents the interaction term of Internet use in time t-1 and the group aged 60 and over dummy. The results are available upon request. ***: p<0.01; **: p<0.05; *: p<0.1.

Table A4. Differences in internet use effect on health status between urban and rural residents.

	(1) Internet_t-1		(2) Urban		(3) Internet_t-1×Urban		
	OR	95% CI	OR	95% CI	OR	95% CI	*N*
SRH	0.840***	(0.75, 0.94)	1.004	(0.94, 1.07)	1.012	(0.89, 1.15)	32731
TMH	0.914	(0.79, 1.05)	0.796***	(0.73, 0.87)	1.192**	(1.01, 1.41)	33155
MH1	0.849*	(0.78, 1.12)	0.790***	(0.70, 0.89)	1.216*	(0.98, 1.51)	32696
MH2	0.926	(0.74, 1.15)	0.772***	(0.67, 0.89)	1.329**	(1.03, 1.72)	32720
MH3	1.109*	(0.98, 1.25)	1.018	(0.95, 1.09)	1.05	(0.92, 1.20)	32721
MH4	0.694**	(0.50, 0.97)	0.902	(0.76, 1.07)	1.12	(0.74, 1.68)	32704
MH5	0.875*	(0.76, 1.01)	0.858***	(0.79, 0.93)	0.987	(0.83, 1.17)	32712
MH6	0.637***	(0.46, 0.87)	0.889	(0.76, 1.03)	1.215	(0.81, 1.88)	32707
LS	1.044	(0.75, 1.37)	1.028	(0.86, 1.22)	1.066	(0.77, 1.47)	33219

Source Calculated based on the data from CFPS of 2014, 2016, and 2018. Note The dynamic LV logistic regression model was used. The Internet use status in time t-1 was used. Covariates including SHR or MH1-6 in time t-1, education, age, age squared term, sex, ethnicity, party, household income, number of family member, marital status, health behavior, social insurance, region (east, central, and west regions) and year dummy variables were estimated, but they were not expressed in the table. The results are available upon request. Internet_t-1×Urban represents the interaction term of Internet use in time t-1 and urban resident dummy. ***: p<0.01; **: p<0.05; *: p<0.1.

References

1. China Network Internet Information Center (CNNIC) (2020). *45th Statistical Report on the Development of the Internet in China*. Beijing: China Network Internet Information Center.
2. Alam, K.; Mamun, S. A. K. Access to Broadband Internet and Labour Force Outcomes: A Case study of the Western Downs Region, Queensland. *Telematics and Informatics*, 2017, 34, 73–84.
3. Dettling. L. J. Broadband in the Labor Market: The Impact of Residential High-Speed Internet on Married Women's Labor Force Participation. *ILR Review*, 2017, 70, 451–82.
4. Krueger, A. B. How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984-1989. *Quarterly Journal of Economics*, 1993,108, 33–60.
5. Zhao, Y. Internet Use and the Well-being of Rural Residents in the Context of Rural Revitalization: An Empirical Study Based on CFPS Panel Data. *Jianghan Academic*, 2021, 40,5–15. (In Chinese).
6. Zhou, X.; Wang, X. The Influence of Internet Usage on the Life Satisfaction of Rural Elderly: Empirical Analysis Based on CLASS 2016 Data. *Journal of Fujian Agriculture for University (Philosophy Social Science)*, 2020, 23,70–80. (In Chinese).
7. Alonzo, A.; Hussain, J.; Strangers, S.; Anderson, K. K. Interplay between Social Media use, Sleep Quality, and Mental Health in Youth: A Systematic Review. *Sleep Medicine Reviews*, 2020, 56, 101414.
8. Chen, L.; Li, Y. Research on Channels of the Impact of Internet Use on Health. *Research on Finance Economics Issues*, 2020, 7, 86–93. (In Chinese).
9. Lu, J.; Wang, B. Research on the Mechanism of Influence of Internet Use on Self-rated Health. *Journal of Sun Yat-Sen University (Social Science Education)*,2020, 60,117–127. (In Chinese).
10. Tavares, A. I. (2020) Self-assessed Health among Older People in Europe and Internet Use. *International Journal of Medical Informatics*, 2020, 141,104240.
11. Zhang, H.; Wang, H.; Yan, H.; Wang, X.. Impact of Internet Use on Mental Health among Elderly Individuals: A Difference in Difference Study Based on 2016-2018 CFPS Data. *International Journal of Environment Research and Public Health*, 2022,19(1), Article no. 101.
12. Zhao, J.; Liu, Z. The Impact of Internet Use on the Health of the Elderly. *China Journal of Population Science*, 2002,5,14–26 (in Chinese).
13. Aggarwal, S. The Long Road to Health: Healthcare Utilization Impacts of A Road Pavement Policy in Rural India. *Journal of Development Economics*, 2021,151, 102667.
14. Verlenden, J.V.; Zablotsky, B.; Yeargin-Allsopp, M.; Peacock, G. Healthcare Access and Utilization for Young Adults with Disability: U.S., 2014–2018. *Journal of Adolescent Health*, 2022, 70(2), 241–248.
15. Bloom, G.; Standing, H.; Lloyd, R. Markets, Information Asymmetry and Health Care: Towards New Social Contracts. *Social Science & Medicine*, 2008, 66(10), 2076–2987.
16. Neves, B.B.; Fonseca, J. R. S. Latent Class Models in Action: Bridging Social Capital & Internet Usage. *Social Science Research*, 2015, 50,15–30.

17. Sun, K.; Zhou, J. Understanding the Impacts of Internet Use on Senior Citizens' Social Participation in China: Evidence from Longitudinal Panel Data. *Telematics and Informatics*, 2021,59, 101566.
18. Geraci, A.; Nardotto, M.; Reggiani,T.; Sabatini, F. Broadband Internet and Social Capital. *Journal of Public Economics*, 2022, 206,.104578.
19. Saadati, H.; Mirzaei, M.; Okhovat, H; Khodamoradi, F. Association between Internet Addiction and Loneliness across the World: A Meta-analysis and Systematic Review. *SSM Population Health*, 2021, 16, 100948.
20. Chen, L.; Li, Y. Research on Channels of the Impact of Internet Use on Health. *Research on Finance Economics Issues*, 2020, 7, 86–93. (In Chinese).
21. Li, L.; Ding, H. The Relationship between Internet Use and Population Health: A Cross-sectional Survey in China. *International Journal of Environmental Research and Public Health*, 2022,19, 1322.
22. Lu, J.; Wang, B. Research on the Mechanism of Influence of Internet Use on Self-rated Health. *Journal of Sun Yat-Sen University (Social Science Education)*, 2020, 60,117–127. (In Chinese).
23. Zhao, J.; Liu, Z. The Impact of Internet Use on the Health of the Elderly. *China Journal of Population Science,* 2020, 5,14–26. (In Chinese).
24. Blomqvist, A. The Doctor as Double Agent: Information Asymmetry, Health Insurance, and Medical Care. *Journal of Health Economics*, 1991,10(4), 411–432.
25. Han, Y.; Chung, R. Y. N. The Role of Neighborhood Social Capital on Health and Health Inequality in Rural and Urban China. *Preventive Medicine,* 2022,156, 106989.
26. Ma, X.; Piao, X.; Oshio, T. Impact of Social Participation on Health among Middle-aged and Elderly Adults: Evidence from Longitudinal Survey Data in China. *BMC Public Health*, 2020, 20(1), 502.
27. Villalonga-Olives, E.; Wind, T.R.; Armand, A.; Yirefu, M.; Smith, R.; Aldrich, D.P. Social Capital Based Mental Health Interventions for Refugees: A Systematic Review. *Social Science & Medicine*, 2022, 301,114787.
28. Geraci, A.; Nardotto, M.; Reggiani,T.; Sabatini, F. (2022). Broadband Internet and Social Capital. *Journal of Public Economics*, 2022, 206, 104578.
29. Shaw, L. H.; Gant, L. M. In Defense of the Internet: The Relationship between Internet Communication and Depression, Loneliness, Self-esteem, and Perceived Social Support. *Cyberpsychol & Behavior*, 2002, 5,157–71.
30. Fatehkia, M.; Kashyap, R.; Weber, I. Using Facebook ad Data to Track the Global Digital Gender Gap. *World Development*, 2018,107,189–209.
31. Haight, M.; Quan-Haase, A.; Corbett, B.A. Revisiting the Digital Divide in Canada: The Impact of Demographic Factors on access to the Internet, Level of Online Activity, and Social Networking Site Usage. Inf. Commun. Soc. 2014,17, 503–519.
32. Organization for Economic Co-operation and Development (OECD). *Bridging the Digital Gender Divide: Include, Upskill, Innovate*. OECD, Paris (2018).
33. Ma, X. Internet Use and Gender Wage Gap: Evidence from China. *Journal for Labor Market Research*, 2022, 56, article15.
34. Nakagomi, A.; Shiba, K.; Kawachi, I.; Ide, K.; Nagamine, Y.; Kondo, N.; Hanazato, M.; Kondo, K. Internet Use and Subsequent Health and Well-being in Older Adults: An Outcome-wide Analysis. *Computers in Human Behavior*, 2022, 130, 107156.
35. Meischke, H.;Eisenberg, M.; Rowe, S.; Cagle, A. Do Older Adults Use the Internet for Information on Heart Attacks? Results from A Survey of Seniors in King County, Washington. *Heart & Lung: The Journal of Acute and Critical Care*, 2005, 34, (1), 3-12.
36. Albarrán, P.; Hidalgo-Hidalgo, M.; Iturbe-Ormaetxe, I. Education and Adult Health: Is There A Causal Effect? *Social Science & Medicine*, 2020, 249, 112830.
37. Hosen, M. J.; Eva, A. S., Rahman, M. M.; Ibrahim, M.; Lira, U. F.; Hossain, A. B.; Shill, M. C.; Uddin, M. J. Health Impacts of Excessive Use of Facebook among University Students in Bangladesh. Heliyon, 2021, 7(6), e07271.
38. Brodersen, K.; Hammami, N.; Katapally, T. R. Is Excessive Smartphone Use Associated with Weight Status and Self-rated Health among Youth? A Smart Platform Study. BMC Public Health, 2023, 23, 234.
39. Sicular, T.; Li, S.; Yue, X.; Sato, H. *Changing Trends in China's Inequality*: *Evidence, Analysis, and Prospects*. Oxford UK: Oxford University Press, 2020.
40. Hindman, D. B. The Rural-Urban Digital Divide. *Journalism & Mass Communication Quarterly*. 2020, 77(3): 549–560.
41. Forman, C.; Goldfarb, A.; Greenstein, S.The Internet and Local Wages: A Puzzle. *American Economic Review*, 2012, 102(1), 556–575.
42. Whitacre, B.; Gallardo, R.; Strover, S. Broadband's Contribution to Economic Growth in Rural Areas: Moving Towards a Causal Relationship. *Telecommunications Policy*, 2014, 38(11), 1011–1023.
43. Ma, X. Internet Use and Income Gaps between Urban and Rural Residents in China. *Journal of the Asia Pacific Economy*, 2022, 29(2), 789–809.
44. Contoyannis, P.; Jones, A. M.; Rice, N. The Dynamics of Health in the British Household Panel Survey. *Journal of Applied Economics*, 2004,19, 473–503.

doi:10.20944/preprints202408.0114.v1

45. Wooldridge, J. M. Econometric Analysis of Cross Section and Panel Data. The MIT Press, 2020.
46. Chen, L.; Li, Y. Research on Channels of the Impact of Internet Use on Health. *Research on Finance Economics Issues*, 2020, 7, 86–93. (In Chinese).
47. Mehta, K.; Arega, H.; Smith, N. L.; Li, K.; Gause, E.; Lee, J.; Stewart, B. Gender-Based Disparities in Burn Injuries, Care and Outcomes: A World Health Organization (WHO) Global Burn Registry cohort study. *American Journal of Surgery*, 2022, 223(1), 157–163.
48. Zhan, P.; Ma, X.; Oshio, T.; Mao, Y. Health Capacity to Work of Older Adults in China. *China Economic Journal*, 2021, 15(1), 2003534.
49. Ma, X. The Impact of Membership of the Communist Party of China on Wages. *Economics Bulletin*, 2019, 39(4), 2839–2856.
50. Ma, X.; Iwasaki, I. Does Party Membership Bring A Wage Premium in China? A Meta-Analysis. J*ournal of Chinese Economics and Business Studies*, 2021,19(1),55–94.
51. Ma. X. *Public medical insurance reform in China*. Singapore: Springer Nature, 2022.
52. Lieber, J.; Clarke, L.; Timæus, I. M.; Mallinson, P. A. C.; Kinra, S. Changing Family Structures and Self-rated Health of India's Older Population (1995-96 to 2014). *SSM Population Health*, 2020,11, 100572.
53. Nie, P.; Clark, A. E.; D'Ambrosio, C.; Ding, L. Income-related Health Inequality in Urban China (1991–2015): The Role of Homeownership and Housing Conditions. *Health Place*, 2022, 73, 102743.
54. Mendoza-Romero, D.; Urbina, A.; Cristancho-Montenegro, A.; Rombaldi, A. Impact of Smoking and Physical Inactivity on Self-rated Health in Women in Colombia. *Preventive Medicine Reports*, 2019,16, 100976.
55. Nolan, A.; May, P.; Matthews, S.; Normand, C.; Kenny, R. A.; Ward, M. Public Health Insurance and Mortality in the Older Population: Evidence from the Irish Longitudinal Study on Ageing. *Health Policy*, 2022,126(3),190–196.
56. Ye, L.; Luo, J.; Shia, B.C.; Fang, Y. Heterogeneous Health Classes for Older Adults and Their Regional Disparities in China: Based on Multidimensional Health. *Health Policy*, 2022,178,15–22.
57. Dettling. L. J. Broadband in the Labor Market: The Impact of Residential High-Speed Internet on Married Women's Labor Force Participation. *ILR Review*, 2017,70, 451–82.
58. World organization. Health (WHO). https://www.who.int/china/health-topics/mental-health [Online Resource]. Accessed February 3, 2022.
59. Bimber, B. Measuring the Gender Gap on the Internet. *Social Science Quarterly*, 2020, 81, 868–876.
60. Li, W.; Cui, Y.; Gong, Q.; Hong, C., Guo, F. The Association of Smartphone Usage Duration with Physical Fitness among Chinese University Students. *International Journal of Environment Research and Public Health*, 2022, 19, 572.
61. Yu, Y.; Mo, P. K. H.; Zhang, J.; Li, J.; Lau, J. T. F. Maladaptive Cognitions, Loneliness, and Social Anxiety as Potential Moderators of the Association between Internet Gaming Time and Internet Gaming Disorder among Adolescent Internet Gamers in China. *Addictive Behavior*, 2022, 129, 107239.