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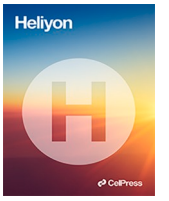

Research article

Does internet use benefit the mental health of older adults? Empirical evidence from the China health and retirement longitudinal study

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ABSTRACT

The mental health (MH) of older adults is a prominent public health concern. However, research regarding the impact of emerging Internet use on MH among older adults remains limited, particularly in transitional economies experiencing a rapidly aging population such as China. Thus, to address this research gap, this study uses data from the 2013–2018 waves of the China Health and Retirement Longitudinal Study. To investigate the causal relationship between Internet use and MH among older adults and explore the underlying channels through which this relationship operates. The results reveal a notable positive association between Internet use and MH among older adults. Furthermore, the study highlights social interaction, social trust, traveling expenses, and healthy habits as crucial channels through which Internet use can impact MH among older adults. The analysis also reveals how Internet use demonstrates a stronger positive effect on older individuals who have fewer chronic diseases and live with their offspring compared with their counterparts. These findings have significant policy implications, which thus emphasizes the need to enhance Internet use among older adults as a means of improving their MH.

1. Introduction

An increasingly aging population has emerged as a substantial challenge across the world; consequently, promoting healthy aging to maintain a high quality of life and independence has become a global concern. The proportion of individuals aged 65 years and above in developed regions is projected to rise from 14.3 % in 2000 to 25.9 % in 2050 [1]. With the advancement of Internet technology, this proportion will grow rapidly. The older population becomes increasingly vulnerable to various health risks and diseases as their life expectancy increases [2]. The existing statistics reveal that the prevalence rates of chronic diseases, disability rates, and the per capita consumption of health resources among older adults are 3.2, 3.6, and 1.9 times higher than those of the total population, respectively [3]. This situation is particularly challenging for China because of its rapid population growth compared with other developing countries. By the end of 2020, the population aged 60 or above in China will reach 264 million, with an aging rate of 18.70 % [4]. The current projections indicate that the proportion of the population over 60 years old in China will reach 34.9 % by 2050,

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ushering the country into a stage of profound aging. Older adults have placed considerable pressure on the healthcare system [5,6]. However, mental health (MH) issues are more serious and less noticeable than physical health problems in older adults. Statistically, half of the adults aged 65–84 years old have experienced MH issues throughout their lives, including depression, loneliness, anxiety, and stress [7]. Poor depression significantly affects the quality of life of older adults and is associated with an elevated risk of mortality and morbidity [8]. Therefore, exploring effective strategies to enhance the MH of older adults is essential.

At present, the Internet has become increasingly popular among older adults following the development of technology and the popularity of smartphones. For instance, 7.3 million senior adults (1.3 % of the senior population) used the Internet in 2009, and the number s went up to 940 million, of which older users (i.e., those over 60 years old) account for 10.3 % [9,10]. The Internet penetration rate of the older adult population aged 60 years and above is 43.2 %. Internet use has substantial effects on reemployment, income enhancement, dietary improvement, and CO_2 emissions among older adults [11–14]. Internet use-based interventions are promising in terms of supporting the health of older adults and have proven to be effective in facilitating lifestyle changes and disease management in countries such as Australia, the Netherlands, and Switzerland [15]. Thus, such interventions might constitute a promising approach for bridging the existing gaps in MH care for older adults in China [16].

Thus far, the existing research has provided some correlational evidence but has yet to arrive at consistent conclusions. Most studies have reliably demonstrated that Internet use offers a convenient and effective means of communication among older adults, thereby enhancing various aspects of their well-being [17–21]. For example, using OLS regressions, Zhang et al. [22] found that Internet use is significantly associated with better MH for older Chinese residents. Clinical data also indicate that Internet use has been effective in reducing anxiety levels among patients with cardiomyopathy (Minto et al. [18]. The reason for such findings is that Internet use could increase life satisfaction, happiness, and overall well-being while concurrently reducing feelings of loneliness, anxiety, stress, and depressive symptoms [23]. Furthermore, the Internet provides an efficient and convenient channel through which older adults can communicate with their friends, fulfill their spiritual needs, enhance their cognitive abilities, and reduce their likelihood of experiencing depression [24]. However, some studies have shown that Internet use has negative implications for older adults in that it reduces social participation, leads to a narrowing of social circles, and weakens friendship networks and the sense of community belonging [4,20,25].

Although existing studies have analyzed the impact of Internet use on MH, few empirical tests have been conducted on the specific channels by which Internet use improves MH and reduces the risk of depression. Social participation serves as an intermediary factor in the relationship between Internet use and the MH of older adults [26–28]. Empirically, Internet use not only improves the self-reported health, MH, and social adaptation of older adults but also enhances their social participation. In particular, Internet use promotes community engagement among older adults, thereby enhancing their life satisfaction and overall health. For instance, Heo et al. [29] report that Internet use reduces loneliness and enhances the life satisfaction and well-being of older adults with social support acting as a mediating variable. Other mediating effects have also been proposed. For example, Cotten et al. [30] demonstrate that household size mediates the positive impact of Internet use among retired adults in the United States, especially for those living alone. Similarly, Yuan [31] reveals that older adults who engage in frequent Internet use are less likely to experience MH issues and identify the moderating effects of chronic diseases and household income on this relationship.

The literature review reveals that there is no current consensus on the influence of Internet use on the MH of older adults, and some limitations are involved. First, most studies have focused on developed countries, such as the United States and New Zealand, and have paid limited attention to developing countries. Such studies have also been based on small samples, thereby limiting the statistical sophistication and robustness of the findings. Second, while earlier studies have separately focused on influence channels by considering the impact of Internet use on social participation, social support, or income, insufficient attention has been paid to social trust and health habits. Previous studies also did not consider these aspects within the same framework to analyze the potential channels of influence. Third, concerning research methodology, the existing studies have mainly focused on simple descriptive statistics and multiple linear regression analysis, which have been criticized for their estimation effectiveness, especially in terms of endogeneity and heterogeneity. Finally, most studies treat older adults as a homogeneous group and report varied, even conflicting, outcomes. Few studies have explored the uneven impact of Internet use on subgroups with different MH conditions.

Therefore, the present research aims to investigate how Internet use affects the MH of older adults based on the 2013–2018 waves of the China Health and Retirement Longitudinal Study (CHARLS). Moreover, we examine whether Internet use has a mediating effect on MH by influencing four key aspects: social interaction, social trust, traveling expenses, and health habits. This study also considers the heterogeneity of older adults in China and analyzes the impact of Internet use on MH among different groups.

Unlike previous studies, this research contributes to the existing literature in the following three aspects. First, using the nationally representative data of the 2013–2018 waves of CHARLS, this study enhances the validity of the estimated causal relationship between Internet use and MH among older adults by addressing endogeneity concerns using the instrumental variable (IV) method. Second, to the best of our knowledge, this is the first study to examine the mediating effect of traveling expenses and consider four key aspects in the same framework to further the existing understanding of the underlying channels between Internet use and MH. Third, we analyze the heterogeneity of the results across the number of chronic diseases that older adults have and their living arrangements (i.e., living with or without their children) to capture the effect of Internet use on these specific groups of older adults. This study offers valuable insights for future research endeavors that aim to explore the relationship between Internet use and MH among older adults in China.

The study is organized as follows. Section 2 presents the data and variables, while Section 3 describes the empirical methods. Section 4 provides the estimation results, and Section 5 discusses the findings based on the empirical results. Finally, Section 6 concludes by summarizing the main findings and proposing policy implications.

2. Data

2.1. Sample

The data used herein are taken from the 2013–2018 waves of CHARLS, a nationally representative longitudinal survey conducted by the Institute of Social Science Survey at Peking University. CHARLS focuses on households and individuals over 45 years of age in China. The survey employs a multistage sampling method with probability proportional to size. The national baseline survey was first conducted in 2011, followed by subsequent waves every 2–3 years. The data from the 2013–2018 waves are the most current data available. Encompassing 150 counties and 450 villages or resident committees in 28 provinces, these waves of the survey included approximately 17,000 individuals from approximately 10,000 households. The questionnaire collects a variety of information, including details on the respondents' socioeconomic status and health circumstances. The CHARLS database is widely recognized as a reliable and valuable source of data within the academic community. According to the 'Law of Protection of Rights and Interests of Older Adults' in the People's Republic of China, individuals over the age of 60 years are considered older adults. Therefore, for the sample, individuals aged 60 years and above in the 2013–2018 waves of CHARLS data are selected. After screening and eliminating samples that lacked relevant variables, a total of 27,561 valid samples were obtained. All data analyses are performed using STATA 16.1 software (STATA Corp. LLC, College Station, TX, USA).

2.2. Variables

2.2.1. Dependent variable

In this study, the dependent variable is MH, specifically referred to as "depression" in the CHARLS dataset. To measure depression, CHARLS uses a simplified version of the Center for Epidemiologic Studies Depression Scale (CES-D10) [32]. This scale comprises eight questions regarding negative emotions and two questions addressing positive emotions. The scale encompasses diverse aspects such as daily mood, loneliness, sleep sufficiency, and the life situation of older adults. The response options, namely, "rarely or none of the time," "some or a little of the time," "occasionally or a moderate amount of the time," and "most or all of the time" are assigned values of 0, 1, 2, and 3, respectively. In contrast, the scores for the positive emotion questions are inversely coded. The sum of the scores for the 10 items ranged from 0 to 30, with higher values indicating higher depression levels. A score of 10 or higher is considered a high depressive level and assigned a value of 1, whereas a score below 10 indicates no depression or a low depressive level and is assigned a value of 0 [33,34]. It should be noted that CES-D10 serves as a preliminary depression screening tool and cannot replace clinical diagnostic conclusions. The reliability coefficients for the CES-D10 items as investigated by Cronbach in 1999 and 2003 are 0.84 and 0.86, respectively [35].

2.2.2. Independent variable

The independent variables examined in this study are Internet use and frequency of Internet use. Owing to data limitations, we examined Internet use and frequency of Internet use for the 2013–2018 waves of the CHARLS questionnaire using the following question, "Have you done any of these activities in the last month?" The question presented 12 response options. The respondents who selected the option "Used the Internet" are classified as Internet users in this study and assigned a value of 1. Otherwise, the respondents are assigned a value of 0 [28,36,37]. The frequency of Internet use variable, as robustness, was examined by the following question, "How often did you use the Internet in the last month?" The response options for this question are categorized as follows: "almost daily" and "almost every week" are assigned a value of 1, whereas "not regularly" is assigned a value of 0.

2.2.3. Channel variables

To comprehend the underlying channels through which Internet use (frequency of Internet use) may impact depression among older adults, variables associated with social interaction, social trust, traveling expenses, and health habits are examined. In the 2013–2018 waves of the CHARLS questionnaire, the variable of social interaction is assessed using the question, "Have you done any of these activities in the last month?" The question included various response options such as "Interacted with friends," "Played Ma-jong, played chess, played cards, or went to a community club," "Provided help to family, friends, or neighbors who do not live with you," "Went to a sport, social, or other kinds of the club," "Took part in a community-related organization," and "Attended an educational or training course." If respondents select any of these options, they are assigned a value of 1; otherwise, they are assigned a value of 0.

The variable of social trust is assessed by asking the following question: "Have you done any of these activities in the last month?" In CHARLS, respondents are asked, "In the last year, how much did your household spend on the following items?" If the answer to this question is greater than 0, a value of 1 is assigned; otherwise, a value of 0 is assigned.

For the variable of travel expenses, we focused on enjoyable consumption such as traveling expenses. The question is "Have you done any of these activities in the last month?" The responses included options such as "Done voluntary or charity work" and "Cared for a sick or disabled adult who does not live with you." Respondents who selected either of these options are assigned a value of 1, whereas others are assigned a value of 0.

The variables of health habits included smoking and physical activity. The responses for smoking are derived from questions such as "Have you ever chewed tobacco, smoked a pipe, smoked self-rolled cigarettes, or smoked cigarettes/cigars?" and "Do you still have the habit, or have you quit?" The status of physical activity is derived by asking, "Do you usually engage in this type of activity for at least 10 min every week?" To measure the variable of health habits, "yes" responses are assigned a value of 1, whereas "no" responses are assigned a value of 0.

2.2.4. Covariates

According to Grossman's health needs theory [38], various factors—such as biological factors, income, social status, education, culture, early child development, health systems, social support, population profiles, and geography—play significant roles in influencing depression. In related studies on Internet use (frequency of Internet use) and depression among older adults, control variables are selected from three dimensions: individual, family, and social characteristics. In this study, the control variables included gender, age, education, marital status, the logarithm of income, the number of chronic diseases, urban residence, insurance, and province and time controls [25,32,36,37]. In addition, given the increasing number of "empty nesters," we took the influence of children on older adults into consideration, and variables such as cohabitation with children and the number of children are also included. These variables are selected because of their close associations with the occurrence of depression symptoms. The data used herein can be obtained from the CHARLS 2013–2018 dataset, although further details are not provided.

3. Empirical method

3.1. Effect of internet use (frequency of internet use) and MH in older adults

To investigate how Internet use (frequency of Internet use) could affect older adults' depression, the panel random effects (RE) Probit model is employed to examine the causality between MH and Internet use (frequency of Internet use) among older adults. This model is established on the basis of the standard normal distribution equation.

$$P(H_{it}=1)=\Phi(\beta_0+\beta_1 I_{it}+\beta_2 Z_{it}) \tag{1}$$

In eq (1), H_i is the MH of the ith older adults in t year, I_{it} represents Internet use (frequency of Internet use), and Z_{it} indicates several control variables to account for potential confounding factors. Eq (1) can be given by:

$$H_{it}^{*}=\alpha_0+\alpha_1 I_{it}+\alpha_2 Z_{it}+\delta_t+\xi_{it}, H_i=1\ (H_i^{*}>0) \tag{2}$$

In eq (2), H_i^{*} is a latent variable, δ_t is a dummy variable that controls the time trend and province, ξ_i symbolizes random disturbance terms, and we can obtain the unbiased estimator $\mathrm{Cov}(I_{it},\xi_{it})=0$. To ensure unbiased and consistent estimation results while addressing potential endogeneity issues, this study used the IV-RE Probit model. The IV-RE Probit model, which corresponds to binary factor variation, is selected as the benchmark for the bivariate panel Probit model. Under the assumption of convergence, employing the IV-RE Probit model for estimation proved to be more efficient. The fundamental concept is to identify instrumental variables that are associated with Internet use (frequency of Internet use) but not with MH and construct an instrumental variable equation to replace the endogenous variables in the equation. The specific implementation process is outlined as follows:

$$H_{it}^{*}=\beta_0+\beta_1 I_{it}+\beta_2 Z_{it}+\delta_t+\xi_{it}\quad H_{it}=1\ (H_{it}^{*}>0) \tag{3}$$

$$\widehat{I_{it}}=\gamma_0+\gamma_1 IV_{it}+\gamma_2 Z_{it}+\xi \tag{4}$$

In eq (3) – eq (4), IV_i indicates the instrumental variables and $\mathrm{Cov}(IV_{it},\xi_i t)=0$, $\mathrm{Cov}(\xi,\xi_{it})=0$, and $\mathrm{Cov}(IV_{it},I_{it})\neq 0$.

3.2. Possible channels explaining the health effects of internet use and frequency of internet use

The other aim of this study is to shed light on the potential channels through which Internet use (frequency of Internet use) affects depression. Some scholars have proposed that the use of stepwise tests for mediating effects should be discontinued and that researchers should refrain from estimating the size of indirect effects or testing their statistical significance [39]. Instead, according to such scholars, the focus of research should shift toward enhancing the credibility of the identified causal relationship between explanatory variable I and explained variable H. As per economic theory, one or several intermediary variables, M, are introduced to reflect the causal pathway from I to H. The impact of M on H should be direct and evident, with an emphasis on identifying the correlation between I and M. In this study, four primary channels, that is, social interaction, social trust, traveling expenses, and health habits, are examined. The model is given as follows:

$$M_{it}=\beta_0+\beta_1 I_{it}+\beta_2 IV_{it}+\beta_3 Z_{it}+\delta_t+\tau_{it} \tag{5}$$

In eq (5), Z_{it} represents the control variable, and M_{it} denotes the mediator variable.

3.3. Identification strategy

Given the longitudinal structure of our data, we can simply run a RE estimation and a fixed effects estimation and use the Hausman test to check which model is preferred. However, we have unbalanced panel data, which suggests that participants are not consistently interviewed or did not consistently respond to the CHARLS questions we are interested in. The fixed effects model assumes that some time-invariant individual characteristics correlate with the predictor or independent variables and may be biased in the estimates. The RE model assumes that variation between individuals is random and uncorrelated with the predictor or independent variables included in the model, unlike the fixed effects model. In this study, the explanatory variable "depression" is a dichotomous variable, so it is

estimated using a panel probit. However, it will lead to an inconsistent estimation of the coefficient α_1 if the fixed effect of the panel probit is estimated. At the same time, the LR test of the RE model in Table 2 rejects the hypothesis of the mixed probit regression model. Therefore, the panel RE probit model is finally selected for estimation. However, the potential endogeneity problem still affects our primary results. Namely, the decision to use the Internet, along with an older individual's depressive symptoms may be determined or influenced by some missing or unobserved variable. In addition, MH conditions affect an older individual's behavior, which in turn may affect their online behavior, creating a reverse causality problem. To overcome these problems and test the main results, we employ the IV-RE probit method to re-estimate the model. This study uses the average Internet use levels of older adults in each village as the instrumental variable of whether the subjects used the Internet or not. The IV-RE probit method is a two-stage regression. In the first stage, the instrumental variables of the principal independent variables are determined and their correlations are evaluated. In the second stage, the instrumental variables are substituted into the model for regression, and the externality of Internet use (frequency of Internet use) is verified according to the endogeneity test parameters.

4. Results

4.1. Statistical description

Table 1 displays the descriptive statistics of the variables, including the number of observations, means, and standard deviations. 36 % of the respondents reported experiencing depression. The independent variable, "Internet", is utilized by 26 % of the older population in the last month, indicating a relatively low prevalence of Internet use among older adults in China. The average frequency of Internet use of the sample is 1.1, with a standard deviation of 0.36. The participants' educational levels range from 0 to 22 years, with an average of 6.6 years of education. The majority of the participants (76 %) are married. Further details of the descriptive statistics are presented in Table 1. Table A1 provides a visual comparison of the differences between Internet users and non-users. The results indicate a statistically significant difference in the level of depression between Internet users (mean = 0.39) and non-users (mean = 0.28). In addition, statistically significant differences are noted in 8 covariates between the aforementioned two groups. It suggests that a causal link between Internet use and depression levels in older adults cannot be extrapolated.

4.2. Baseline regression

Using the panel RE Probit model, Table 2 presents the impact of Internet use and frequency of Internet use on MH. In Model (1), Internet use demonstrates a significant negative coefficient of −0.401 ($p < 0.01$), indicating that it reduces depression levels. Model (2) yields consistent results even after incorporating covariates, thus highlighting the significantly negative relationship between the selected control variables and depression with a coefficient of −0.300. To minimize the bias of analysis results, we also consider the frequency of Internet use in the baseline regression analysis. Model (3) in Table 2 presents the estimated results of the frequency of Internet use variable. The results show that the coefficient is estimated as −0.432 thus indicating a statistically significant impact at the 1 % level. Upon incorporating covariates, Model (4) displays consistently significantly negative results with a coefficient of −0.261. It

Table 1
Descriptions and basic statistics of the selected variables.

Variables	Definition	Mean	S.D.
Dependent variable			
MH	If high depressive level = 1, otherwise = 0	0.36	0.48
Independent variable			
Internet	If individual uses Internet = 1, otherwise = 0	0.26	0.44
Fre_internet	The frequency of Internet use, If not regularly = 1, If almost every week = 2, If almost daily = 3	1.1	0.36
Channel variables			
Social	Joining social activities	0.46	0.50
Trust	Trust others including strangers	0.03	0.16
Traveling expenses	Long-distance traveling expenses	0.37	0.48
Smoke	Smoking	0.34	0.47
Physical activities	Doing physical activities every week	0.57	0.49
Control variables			
Gender	If male = 1, otherwise = 0	0.50	0.50
Age	Years of age	70	7.40
Age^2	Age squared	4885	1079
Education	Years of education	6.60	5.00
Married	If married = 1, otherwise = 0	0.76	0.42
Lincome	The Logarithm of respondent's income in the last year (yuan)	5.50	3.10
Illness	Numbers of chronic diseases	1.30	1.40
Urban	If currently living in urban = 1, otherwise = 0	0.39	0.49
Living with child	If living with child = 1, otherwise = 0	0.40	0.49
Child number	Numbers of children	1.90	2.00
Insurance	If had basic endowment insurance = 1, otherwise = 0	0.32	0.46
Observations: 27,561			

Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

Table 2
Baseline regression results of the effect of Internet use and frequency of Internet use on MH.

Variables	(1)	(2)	(3)	(4)
Internet	−0.401***	−0.300***		
	(0.027)	(0.028)		
Fre_internet			−0.432***	−0.261***
			(0.036)	(0.036)
Gender		−0.413***		−0.408***
		(0.026)		(0.026)
Age		0.155***		0.160***
		(0.026)		(0.026)
Age^2		−0.001***		−0.001***
		(0.000)		(0.000)
Education		−0.012***		−0.012***
		(0.003)		(0.003)
Married		−0.166***		−0.171***
		(0.031)		(0.031)
Lincome		−0.018***		−0.018***
		(0.005)		(0.005)
Illness		0.131***		0.132***
		(0.008)		(0.008)
Urban		−0.334***		−0.363***
		(0.028)		(0.028)
Living with child		0.066***		0.013
		(0.023)		(0.023)
Child number		−0.026***		−0.022**
		(0.010)		(0.010)
Insurance		−0.254***		−0.252***
		(0.034)		(0.034)
Province and time fixed effect	Yes	Yes	Yes	Yes
lnsig2u	0.032	−0.221***	0.056	−0.203***
	(0.045)	(0.049)	(0.045)	(0.049)
LR test	1741.13***	1221.59***	1800.37***	1252.35***
N	27,561	27,561	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

suggests that introducing control variables can effectively reduce estimation bias. This finding supports the notion that Internet use can effectively decrease depression levels and enhance MH.

4.3. Accounting for the endogeneity of internet use and frequency of internet use

For the instrumental variable, this study selects the average Internet use levels of older adults in each village or community, excluding the individuals being analyzed. Using high-level average values (e.g., province- or community-level ones) as instruments for lower levels (e.g., the household level) is a common technique in the literature [40–42]. The reliability of the IV estimation depends on the validity of the instrumental variable. The instrumental variable should be highly correlated with the endogenous variable but has

Table 3
IV estimation of the impact of Internet use and frequency of Internet use on MH.

Variables	(1)	(2)
Second stage:		
Internet	−0.581***	
	(0.077)	
Fre_internet		−1.351***
		(0.117)
Controls[a]	Yes	Yes
Province and time fixed effect	Yes	Yes
First stage:		
IV	−0.739***	−0.325***
	(0.016)	(0.014)
Wald test	19.52***	43.95***
AR	57.65***	60.08***
Wald	57.35***	55.50***
N	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a] Controls include all control variables as in Table 2.
Source: Authors' calculation based on the CHARLS data from 2013 to 2018 waves.

no direct correlation with the dependent variable. First, it satisfies the correlation requirement. Following behavioral imitation theory, a higher Internet use rate among older adults in a given village increases the likelihood and the frequency of individual Internet use due to spillover effects. Second, it is deemed exogenous. Internet use by others in the same village is unlikely to have a direct impact on individual behavior and depression. Hence, the average Internet use rate is considered an ideal instrumental variable. The CHARLS samples are categorized according to village/residence code, and the average Internet use rate of older adults in each village or neighborhood committee is calculated as the regional-level Internet use rate. The strength of the instrumental variable is assessed using the *p*-value. If it is significant at the 1 %, 5 %, or 10 % levels, the absence of a weak instrumental variable problem in the regression is indicated. This approach ensures that the instrumental variable selected is strongly correlated with the dependent variables and does not introduce bias into the result estimators.

Of the various methods used to establish causality, IV analysis offers distinct advantages in terms of addressing endogeneity. To address endogenous issues, this study employs an IV-RE approach for a comprehensive analysis. In the first stage of the regression, as shown in Table 3, the instrumental variable is statistically significant and negatively correlated with Internet use and the frequency of Internet use thus meeting the dependency condition of the instrumental variables. The *p*-value of the weak IV test is significant at the 1 % level. Rejecting the null hypothesis (null hypothesis H_0: endogenous variables are not correlated with instrumental variables), indicates that the instrumental variables are not weak. Thus, the instrumental variable is valid and can be used in further estimations.

Following the findings in Model (1)–(2) of Table 3, Internet use and the frequency of Internet use exhibit statistical significance ($p < 0.01$) for depression among older adults. These findings indicate that a higher level of Internet use or a higher frequency of Internet use has a negative impact on depression among older adults, which is consistent with the results obtained from the baseline regression analysis. It is similar to the results of previous studies [36,43].

4.4. Robustness test

To ensure the robustness of the findings, three additional methods are used to conduct robustness tests. To explore the robustness of the depression variable, the measurement of the independent variable is changed to a continuous variable Table 4 presents the estimated results after substituting the measurement of the dependent variable for robustness testing. According to the results, the effect is statistically significant at the 1 % level. This finding further supports the notion that Internet use (frequency of Internet use) enhances the MH of older adults, which is consistent with the results obtained from the baseline regression analysis.

According to the age criteria defined by the World Health Organization for the older population, individuals aged 85 years and above are considered to be long-lived older adults. Thus, to account for the potential impact of extreme age values, individuals exceeding 85 years of age are excluded from this analysis, and the robustness of the results is re-estimated. Table 5 shows that the estimated marginal effects are −0.570 and −0.811, demonstrating statistical significance at the 1 % level. These results are consistent with previous research findings; thus reinforcing the robustness of the observed relationship between Internet use (frequency of Internet use) and MH outcomes among the older population.

To address potential self-selection bias and reverse causality, the endogenous switching probit (ESP) method is employed for in-depth analysis. This approach accounts for the possibility that Internet use among older adults may result from self-selection and that there could be a bidirectional relationship between Internet use and MH. The ESP model has been designed to mitigate bias due to observable and unobservable factors [44,45]. To control for self-selection bias, the IV method is employed to correct for any potential bias [46].

The estimation results of the ESP model are presented in Table A2. The average Internet use of other older adults within the same village had a significant positive effect on an individual's likelihood of using the Internet. This suggests that a higher average level of Internet use among older adults in the same village increases the probability of individual Internet adoption. The parameter ρ_1 is statistically significant at the 1 % level, indicating the presence of selective bias in the regression model. Unobservable factors impact both the level of Internet access and the MH of older adults. Furthermore, ρ_1 determined to be positive, suggesting that the MH level of

Table 4
IV estimation of the impact of Internet use and frequency of Internet use on MH.

Variables	(1)	(2)
Second stage:		
Internet	−0.248**	
	(0.232)	
Fre_internet		−0.522***
		(0.109)
Controls[a]	Yes	Yes
Province and time fixed effect	Yes	Yes
First stage:		
IV	−0.353***	−0.353***
	(0.247)	(0.446)
F value	20.79	62.87
N	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a] Controls include all control variables as in Table 2.
Source: Authors' calculation based on the CHARLS data from 2013 to 2018 waves.

Table 5
Robustness test results of MH consequences of Internet use and frequency of Internet use.

Variables	(1)	(2)
Second stage:		
Internet	−0.570***	
	(0.083)	
Fre_internet		−1.263***
		(0.186)
Controls[a]	Yes	Yes
Province and time fixed effect	Yes	Yes
First stage:		
IV	−0.773***	−0.555***
	(0.018)	(0.025)
Wald test	18.86***	37.97***
AR	47.80***	49.99***
Wald	47.43***	46.09***
N	21,833	21,833

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a] Controls include all control variables as in Table 2.
Source: Authors' calculation based on the CHARLS data from 2013 to 2018 waves.

older adults using the Internet is higher than that of the overall sample. The goodness-of-fit test and model independence are statistically significant at the 1 % level, indicating that the use of the ESP model is appropriate.

The ESP model is selected to empirically analyze the impact within a "counterfactual" framework, allowing for the calculation of the average treatment effect on the treated (ATT), average treatment effect on the untreated (ATU), and average treatment effect (ATE) [47]. However, because the ATU and ATE parameters include the effects on samples unaffected by joining cooperatives, this study focuses solely on the ATT, representing the mean change in the MH status of the sample using the Internet compared with that if they did not use the Internet. Table 6 presents the estimated treatment effects of Internet use on MH behaviors among older adults. The treatment effect is consistent with the previously estimated results, indicating that Internet use can significantly improve MH among older adults. The results obtained from the ESPmodel provide additional support for the robustness of the findings.

4.5. Heterogeneity analysis

In the previous study, researchers treated all older adults as a homogeneous group when examining the average effect of Internet use (frequency of Internet use) on MH. However, the Internet use (frequency of Internet use) of different older groups with varying individual characteristics is heterogeneous is notable. Previous studies have demonstrated the impact of Internet use (frequency of Internet use) on depression across various demographic groups [44,48,49], which differ in terms of income level, gender, education level, age, and number of accompanying persons [50–52]. However, limited evidence exists regarding the differences observed among groups based on their physical health status or living arrangements. To investigate the effects of Internet use (frequency of Internet use) on MH among older individuals with different characteristics, we examine the regression results of variables such as the number of chronic diseases and living arrangements (specifically, living with children). Moreover, the analysis employs the IV-RE method to address any potential endogeneity issues.

Table 7 presents the findings of the heterogeneity analysis between Internet use and depression. In Model (1), the effect of the interaction between Internet use and living arrangements (whether the respondents are living with their children) on depression is examined. The findings demonstrate a significant negative interaction effect, suggesting that the relationship between Internet use and depression is attenuated among older adults who cohabit with their children. In other words, Internet use is more likely to be associated with better MH among individuals living with their children. In Model (2), the effect of the interaction between Internet use and the number of chronic diseases on depression is investigated. The results reveal a significant positive interaction, suggesting that the association between Internet use and depression is stronger among older adults with a lower number of chronic diseases, which indicates that healthier older individuals tend to experience greater benefits from Internet use than those with poorer health conditions. Model (3) incorporates both of these interaction terms, and the results align with those of Models (1) and (2). Thus, it can be concluded that the Internet has the potential to reduce MH disparities among the older adult population. Notably, this effect tends to be significantly positive for older adults with fewer chronic diseases who live with their children. Table A3 presents the findings of the

Table 6
The treatment effect of Internet use on older adults' MH.

Variables	Observations	Mean	S.D.	Min	Max
ATT	7053	−0.192	0.039	−0.334	−0.050
ATU	20,508	−0.167	0.042	−0.296	0.001
ATE	27,561	−0.173	0.039	−0.298	0.003

Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

Table 7
Heterogeneity analysis of Internet use and MH.

Variables	(1)	(2)	(3)
Internet	−0.709***	−1.092***	−1.235***
	(0.104)	(0.082)	(0.110)
Inter1	−0.285***		−0.326***
	(0.073)		(0.074)
Inter2		0.357***	0.356***
		(0.021)	(0.021)
Controls[a]	Yes	Yes	Yes
Province and time fixed effect	Yes	Yes	Yes
First stage:			
IV	0.511***	0.749***	0.518***
	(0.017)	(0.017)	(0.018)
IV1	0.569***		0.569***
	(0.015)		(0.015)
IV2		−0.007***	−0.006***
		(0.005)	(0.006)
Wald test	18.62***	244.97***	242.17***
AR	57.76***	369.39***	368.50***
Wald	57.43***	358.03***	356.84***
N	27,561	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a] Controls include all control variables as in Table 2.
Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

heterogeneity analysis between the frequency of Internet use and depression. The results are consistent with the above findings.

4.6. Channel analysis

Based on the available data, this study examines the potential channels through which Internet use (frequency of Internet use) affects MH among older adults. Specifically, the study focuses on investigating the roles of social interaction, social trust, traveling expenses, and health habits in this relationship. The relevant variables are obtained from CHARLS 2013–2018 waves, as detailed earlier in this article. Table 8 presents the estimations for the effects of Internet use through these channels. Consistent with Gatto et al. [53], Model (1) examines the mediating effect of social interaction. The results indicate that the regression coefficient of Internet use is significantly positive at the 1 % level, indicating that Internet use promotes social interaction among older adults. In Model (2), the mediating effect of social trust is examined the results showed a significantly positive regression coefficient for Internet use at the 1 % level indicating that Internet use promotes social trust among older adults. Models (4) analyze the mediating effect of health habits. Health habits, especially physical exercise, stimulate dopamine secretion, which is a positive factor for MH. The results show that the Internet has a significantly positive impact at the 1 % level on physical exercise. In Model (5), the mediating effect of smoking is also examined, the results showed a significantly negative regression coefficient for Internet use at the 1 % level. This indicates that Internet use decreases smoking behavior among older adults.

Previous studies have implied that a higher level of Internet use is associated with a higher likelihood of traveling [54,55]. Furthermore, studies have shown that traveling can reduce anxiety, which is a positive factor for MH [56,57]. Based on this evidence, this study hypothesized that Internet use may affect MH by improving traveling expenses. To test this hypothesis, traveling expenses

Table 8
The estimations for the effects of Internet use on potential channels.

Variables	(1)	(2)	(3)	(4)	(5)
	Social	Trust	Traveling expenses	Sport	Smoke
Internet	0.633***	0.686***	0.181***	0.228***	−0.358***
	(0.072)	(0.140)	(0.089)	(0.079)	(0.085)
Controls[a]	Yes	Yes	Yes	Yes	Yes
Province and time fixed effect	Yes	Yes	Yes	Yes	Yes
First stage:					
IV	0.738***	0.738***	0.739***	0.739***	0.739***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Wald test	44.85***	16.67***	300.21***	8.05***	12.23***
AR	78.30***	24.24***	465.31***	8.32***	17.89***
Wald	76.75***	24.05***	408.64***	8.28***	17.79***
N	27,561	27,561	27,561	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a] Controls include all control variables as in Table 2.
Source: Authors' calculation based on the CHARLS data from 2013 to 2018 waves.

are used as a potential channel. In Model (3), the mediating effect of traveling expenses is examined. Internet use significantly increased traveling expenses and increased the enjoyment of older adults' lives. Based on the available data, this study examined the potential pathways through which Internet use influences MH among older adults. Specifically, the study focused on investigating the role of social interaction, social trust, traveling expenses, and health habits (i.e., smoking and exercise) in this relationship. Table A4 presents the findings of the analysis of the potential channel between the frequency of Internet use and the channel variable. The results are consistent with the above findings.

5. Discussion

In the context of an increasingly aging population, the comprehensive utilization of the Internet has emerged as a crucial approach to promoting healthy aging and enhancing the MH of older adults. In this study, the majority of the older adults in our sample did not use the Internet. Although not being able to use the Internet is currently the norm for older people in China, the proportion of Internet users has witnessed a rapid increase. These results are consistent with previous research highlighting the relationship between socioeconomic status and Internet use. In recent years, the relationship between Internet use and MH has been a topic of discussion among scholars. Thus, in this study, we investigated the effects of Internet use (frequency of Internet use) on MH among older individuals in China through a systematic empirical analysis. Our results found that Internet use (frequency of Internet use) had a significant negative impact on depression in older adults in China. After controlling for demographic variables and overcoming endogenous problems, these effects remain significant. These results support previous findings that Internet use is associated with lower depression levels and better MH (Lagoe et al., 2015; [19,31]).

Our findings indicated that the relationship between Internet use (frequency of Internet use) and MH is influenced by mediating factors such as social interaction, social trust, traveling expenses, and health habits (i.e., smoking and exercise). First, having a robust social network is crucial for older adults to engage in economic activities [19,58]. A well-developed social network can considerably improve their willingness to integrate into society, slow down cognitive decline, and contribute to better MH, which aligns with social support theory. Furthermore, Internet use (frequency of Internet use) compensates for the growing lack of social connections among older adults because it allows them to expand their social circles easily and rapidly. Second, the widespread adoption of the Internet has brought remarkable changes to information acquisition and social communication patterns, subsequently affecting social trust [59]. Internet use (frequency of Internet use) contributes to an increased frequency of contact with the outside world among older adults, fostering a sense of identity and trust in various social groups. Regular Internet users among older adults can gain trust and engage in social activities more conveniently. Moreover, the "echo chamber" effect within online networks improves users' overall trust in society. Third, according to the theory of rational behavior, individual decision-making is an analytical judgment based on known information. Access to the Internet enables older adults to acquire extensive enjoyment knowledge such as travel-related information. The abundance of online information can change their consumption behavior and turn them into pleasure-oriented consumers, particularly for traveling purposes. It broadens the horizons of older adults as it allows them to explore and embrace a more fulfilling life. Finally, health habits in an Internet-based environment can improve the MH of older adults through internal physical health adjustment [36]. This is because health habits, especially exercise, can alleviate emotional states such as anxiety, stress, and depression through physiological and biochemical mechanisms [60].

Moreover, our findings reveal that Internet users experience a significant positive effect on MH, particularly among older adults with a lower number of chronic diseases, who also exhibit reduced levels of depression. Older adults with better physical health and greater adaptability tend to exhibit more enthusiasm and happiness in terms of engaging in online social activities facilitated by the Internet. Consequently, Internet use (frequency of Internet use) may effectively reduce MH issues within this healthier older group. In contrast, unhealthy older adults may derive fewer psychological benefits from Internet use (frequency of Internet use) because of their compromised physical health. In addition, our results indicate that the Internet has a stronger positive impact on MH among older adults living with their children. This suggests that Internet use may be particularly effective in mitigating MH problems among older adults who have more companionship from their children. Internet use also provides a novel means of communication for older adults as it enables them to maintain familial relationships and access emotional support from family and friends. This opportunity is particularly valuable for older adults with better health who reside with their children.

6. Conclusions

In this study, we empirically analyzed the 2013–2018 waves of CHARLS data to examine the impact of Internet use on MH among older adults. Internet use had a statistically significant positive effect on MH among older adults. Moreover, Internet use significantly and positively impacted social interaction, social trust, traveling expenses, and health habits, which acted as intermediaries in improving MH outcomes. Finally, Internet use exhibited a more pronounced positive effect on MH among older individuals who resided with their children and had fewer chronic diseases. This study provided a thorough analysis of the impact of Internet use on MH among older adults in China. Our findings hold notable implications for promoting Internet use not only in China but also in other developing countries seeking to improve MH among older adults.

This study contributes considerably to the existing literature by providing valuable insights into the impact of Internet use on MH among older adults, specifically regarding depression. Moreover, it sheds light on the fact that the findings in this area have been inconsistent and therefore warrant attention from academia. With China experiencing a growing trend of population aging and increasing residential separation between children and parents, this research aligns with societal expectations and addresses the need to understand the impact of Internet use on the psychological well-being of older adults. The desire among older adults to defy aging

and engage with the outside world through various media platforms to lead fulfilling and enjoyable lives underscores the practical significance of this research. To the best of our knowledge, this study is the first to examine the mediating effect of traveling expenses on the relationship between Internet use and MH among Chinese older adults. It is also the first study to take four aspects into account in the same framework to analyze the potential channels of influence.

Our findings have profound implications from practical and policymaking perspectives. Although the adoption of the Internet among older adults in China remains relatively low, our results have important policy implications for promoting MH among this population, thereby enabling the benefits of information development to reach a wider audience. First, enhancing the accessibility and popularity of Internet use among older adults is crucial, especially in rural areas. This can be achieved by bolstering the development of public Internet services, improving the availability of Internet resources for older adults, and encouraging an equitable distribution of Internet resources. Second, efforts should be made to stimulate the enthusiasm of older adults for using the Internet and enhance their Internet literacy. Local governments and communities can play a vital role by providing tailored online education programs and removing technological barriers that impede older adults from using the Internet. Internet education disseminates information and contributes to preventing and reducing the incidence of chronic diseases, thereby reducing personal and social care costs. Moreover, the Internet can improve the information processing skills of older adults and mitigate their distrust of the Internet. In addition, fostering a social and familial environment conducive to Internet use among older adults allows more adults to benefit from the advantages of the information age, enhance their social participation, alleviate their loneliness, and mitigate the pressures of aging. Last but not least, the Internet can serve as an intervention tool to address issues related to depression. Local governments, civil organizations, and universities can incorporate depression relief initiatives into their social service programs to improve the quality of life of older adults. Furthermore, Internet technology can be used as a complementary treatment approach for adults with MH issues, including depression.

Nevertheless, it is imperative to recognize the limitations inherent in this study. First, the generalizability of our findings may be limited owing to the specific characteristics of the sample used in this analysis. It is important to exercise caution when generalizing our findings to the present context because the rapid advancements in the Internet in recent years may have resulted in substantial changes in Internet usage patterns among older adults in China, which could have impacted our findings. Future research should strive to enhance the robustness of the findings by using a larger sample size and the latest data. This would further validate the relationship between Internet use and depression among older adults. In addition, our study focuses solely on the overall impact of Internet use on depression among older adults, without considering the specific functions or features of the Internet. Exploring the effects of different Internet functionalities on depression outcomes is an important avenue for future research. By investigating specific aspects of Internet use, such as social media, online support groups, or telemedicine, researchers can gain an in-depth understanding of how different technological features contribute to depression outcomes among older adults. These limitations provide valuable insights for future research endeavors and highlight areas that should be further explored and expanded upon. Future research can address these limitations to yield more comprehensive and nuanced insights into the relationship between Internet use and depression among older adults.

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Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Lixia Zhang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shaoting Li:** Writing – review & editing, Visualization, Software, Resources, Methodology, Formal analysis. **Yanjun Ren:** Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Descriptive statistics for the sample.

Variables	Internet non-user	Mean	Internet user	Mean	MeanDiff
Depression	20,508	0.39	7053	0.28	0.11**
Gender	20,508	0.50	7053	0.50	0.00
Age	20,508	69.93	7053	68.25	1.68***
Age^2	20,508	4946.45	7053	4707.78	−238.67***
Education	20,508	6.32	7053	7.55	−1.23***
Married	20,508	0.75	7053	0.81	−0.06***
lnincome	20,508	5.13	7053	6.44	−1.30***
Illness	20,508	1.34	7053	1.09	0.25
Urban	20,508	0.33	7053	0.59	−0.26***
Living with child	20,508	0.35	7053	0.57	−0.23***
Child number	20,508	2.13	7053	1.16	0.97*
Insurance	20,508	0.29	7053	0.38	−0.09***

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

Table A2
The estimations of MH consequences of Internet use using the ESP model.

Variables	Internet	Depression_1	Depression_0
IV	0.255***		
	(0.062)		
Gender	−0.048**	−0.269***	−0.319***
	(0.020)	(0.035)	(0.019)
Age	−0.142***	0.108***	0.127***
	(0.019)	(0.039)	(0.021)
Age^2	0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
Education	0.029***	−0.016***	−0.006**
	(0.002)	(0.005)	(0.003)
Married	0.039	−0.100**	−0.124***
	(0.025)	(0.046)	(0.023)
lnincome	0.008**	−0.013**	−0.015***
	(0.004)	(0.007)	(0.004)
Illness	−0.014*	0.120***	0.122***
	(0.007)	(0.013)	(0.007)
Urban	0.058**	−0.135***	−0.208***
	(0.023)	(0.043)	(0.023)
Living with child	0.702***	0.134***	0.115***
	(0.019)	(0.046)	(0.025)
Child number	−0.047***	−0.040**	−0.020***
	(0.009)	(0.019)	(0.008)
Insurance	0.213***	−0.226***	−0.157***
	(0.028)	(0.048)	(0.034)
Province and time fixed effect	Yes	Yes	Yes
ρ1	0.152***		
	(0.066)		
ρ0	0.191***		
	(0.055)		
LR test	17.28***		
N	27,561		

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

Table A3
Heterogeneity analysis of the frequency of Internet use and MH.

Variables	(1)	(2)	(3)
Fre_internet	−1.281***	−1.553***	−1.472***
	(0.177)	(0.182)	(0.178)

(*continued on next page*)

Table A3 (*continued*)

Variables	(1)	(2)	(3)
Inter1	−0.049**		−0.050***
	(0.019)		(0.019)
Inter2		0.115***	0.114***
		(0.007)	(0.007)
Controls[a]	Yes	Yes	Yes
Province and time fixed effect	Yes	Yes	Yes
First stage:			
IV	0.358***	0.331***	0.366***
	(0.016)	(0.015)	(0.016)
IV1	−0.073***		−0.074***
	(0.013)		(0.013)
IV2		−0.005***	−0.006***
		(0.005)	(0.005)
Wald test	52.96***	49.69***	57.89***
AR	60.29***	368.20***	367.03***
Wald	56.13***	340.25***	341.90***
N	27,561	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a]Controls include all control variables as in Table A2.
Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

Table A4
The estimations for the effects of frequency of Internet use on potential channels.

Variables	(1)	(2)	(3)	(4)	(5)
	Social	Trust	Traveling expenses	Sport	Smoke
Fre_internet	1.458***	1.479***	4.068***	0.522***	−0.814***
	(0.172)	(0.323)	(0.252)	(0.181)	(0.195)
Controls[a]	Yes	Yes	Yes	Yes	Yes
Province and time fixed effect	Yes	Yes	Yes	Yes	Yes
First stage:					
IV	0.324***	0.324***	0.325***	0.324***	0.324***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Wald test	57.44***	16.03***	398.12***	6.76***	16.21***
AR	79.74***	21.59***	458.59***	8.43***	17.88***
Wald	72.07***	20.95***	261.04***	8.32***	17.33***
N	27,561	27,561	27,561	27,561	27,561

Note: Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a]Controls include all control variables as in Table A2.
Source: Authors' calculation based on the CHARLS data from the 2013–2018 waves.

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