Does Digital Technology Reduce Health Disparity? Investigating Difference of Depression Stemming From Socioeconomic Status Among Chinese Older Adults

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Abstract

Background: Prior studies on health disparity have shown that socioeconomic status is critical to inequality of health outcomes such as depression. However, two questions await further investigation: whether disparity in depression caused by socioeconomic status will become larger when depression becomes severer, and whether digital technology will reduce the disparity in depression caused by socioeconomic status. Our study aims to answer the above two questions.

Methods: By using the dataset from China Health and Retirement Longitudinal Study 2015, we use quantile regression models to examine the effect of socioeconomic status on depression across different quantiles, and test the moderating effect of digital technology.

Results: Our study obtains four key findings. First, the negative effects of socioeconomic status on depression present an increasing trend at high quantiles. Second, Internet usage exacerbates the disparity in depression caused by education level on average, but reduces this disparity caused by education level at high quantiles. Third, Internet usage reduces the disparity in depression caused by income on average and at high quantiles. Fourth, mobile phones have almost no moderating effect on the relationship between socioeconomic status and depression.

Conclusions: Our findings suggest the potential use of digital technology in reducing disparity in depression caused by socioeconomic status among middle-aged and aged

individuals in developing countries.

Keywords: Diversity in aging; Mental health; Digital Technology

Introduction

Depressive symptoms are characterized by persistent sadness and a loss of interest in all or almost all activities, accompanied by the syndromes, such as weight loss or gain, which last at least 2 weeks (Alexopoulos, 2005). Depressive disorder, which has been suffered by 300 million people worldwide in 2015, is one of the main leading causes of further increase in the number of all-age years lived with disability (YLDs) in 1990 up to 2017 (James et al., 2018). Depression is particularly acute in the elderly and in low- and middle-income countries (LMICs) (World Health Organization, 2017) With the high prevalence of depression in the elderly and the continuous aging of people aged 45-55 years, the health system of all countries faces major challenges to ensure the well-being of aging individuals (Lee & Mason, 2011), especially in LMICs. In China, the depression prevalence rates of middle- and old-aged individuals are quite high, with the overall prevalence of depression ranging from 11% to 57% among people aged over 60 years (Chen, Hicks, & While, 2012). Previous studies have concluded that socioeconomic status (SES) is a strong predictor of depression (Domènech-Abella et al., 2018; Lei, Sun, Strauss, Zhang, & Zhao, 2014). However, these findings are difficult to guide us in direct health interventions because we can hardly change SES. In other words, disparity in depression caused by SES is deep-rooted and will persist. In this case, a key question is: can we weaken this deep-rooted disparity in depression through feasible means?

Digital technology, which is characterized as low cost and easy accessibility, has considerable potential to deliver public health intervention (Bennett & Glasgow, 2009). Thus far, positive outcomes have been reported in randomized controlled trails of digital interventions across a wide range of clinical outcomes, including mental health disorders (Deady et al., 2017; Mohr, Burns, Schueller, Clarke, & Klinkman, 2013).

Recent systemic review of evidence has shown promise for use of digital technology to manage depression prevalent among older adults (Chipps, Jarvis, & Ramlall, 2017). Though prior studies have examined the direct effect of digital technology on depression, few of them considered the moderating effect of digital technology. Instead, this paper focuses on the moderating effect and investigates whether digital technology can weaken the deep-rooted disparity in depression caused by SES.

This study uses a quantile regression approach to provide a holistic view of how SES influences depression and how digital technology moderates the relationship between SES and depression. Our methodology has two advantages. First, quantile regression outperforms OLS for skewed distributed dependent variable. Our data are from China Health and Retirement Longitudinal Study 2015, in which the distribution of depression is right skewed. Thus, conditional mean cannot well describe the relationship between SES and depression, which makes ordinary least squares (OLS) estimates unsatisfactory. Second, quantile regression has been widely used to examine health disparity since it can provide a holistic view of the relationship between two variables (Cook & Manning, 2009; Gebregziabher et al., 2011). Quantile regression model provides us the capability to “think beyond the mean”. From a practical point of view, we are particularly concerned about the situation of severe depression. Consequently, we adopt the quantile regression approach and answer two research questions: (1) Will the disparity in depression caused by socioeconomic status expand under severe depression cases? (2) Will digital technologies reduce the disparity in depression caused by socioeconomic status at different quantiles?

Theoretical Background and Hypotheses

Socioeconomic status is essential social origin of disparity in depression (Pearlin,

Menaghan, Lieberman, & Mullan, 1981; Wheaton, 2010). In addition to education and income, which are widely recognized causes of health disparity (Herd, Goesling, & House, 2007; McEniry, Samper-Ternent, Flórez, Pardo, & Cano-Gutierrez, 2018), recent studies have found that childhood conditions also affect aging health. Low level of parental education and self-rated health status during childhood are associated with depression in later life (Carr, 2019; Andrade & Quashie, 2016). In Chinese context, hukou (household registration) status, which is categorized into agricultural or non-agricultural, is related to the availability of a wide range of social benefits. Individuals with agricultural hukou are faced with constraints in education resources, housing, and jobs compared with non-agricultural hukou (Norstrand & Xu, 2011). A recent meta-analysis also shows that the prevalence of depression in rural older adults is significantly higher than in urban areas (Zhang, Xu, Nie, Zhang, & Wu, 2012). Basing on these arguments, we propose that individual SES, which include parental education, self-rated health status during childhood, education, income, and hukou, have a negative impact on depression in later life. Depression status, in this study, is measured by The Center for Epidemiological Studies-Depression Scale (CES-D). The higher the score is, the severer the depression. Thus, our hypothesis is

H1: Individual SES is negatively associated with depression in later life.

We focus on subgroups with severe depressive status, which have higher CES-D score, by estimation at high quantiles to examine association with individual SES. We propose that the disparity in depression may be larger among subgroups of older adults with severe depression status. Thus, we hypothesize the following:

H2: Disparity in depression caused individual SES is larger among higher quantile-level subgroups.

In the context of “formed” individual SES, human agency and resource mobilization may reshape the outcomes (Wheaton, 2010). The growing Evidences suggest that digital technology usage is a significant predictor of higher levels of social support, reduced loneliness, and better life satisfaction and psychological well-being among older adults (Szabo, Allen, Stephens, & Alpass, 2018; Sims, Reed, & Carr, 2016). Digital technology as available resources play a significant role in reducing health disparity caused by location (Goh, Gao, & Agarwal, 2016) and helping patients move to healthy status (Yan, 2018). Thereby, we argue that in the context of SES leading to health disparity, digital technology usage will alleviate the inequality of depression caused by SES. We only consider individual SES factors that have been formed and are interferable at this stage, such as education, income, and hukou. In other words, digital technology usage negatively moderates the relationship of “formed” and “interferable” individual SES, including education, income, and hukou, to depression. Thus, we hypothesize the following:

H3: Digital technology usage negatively moderates the relationship of individual SES and depression.

Digital technology have a long-term effect on alleviating loneliness for elderly (Tsai & Tsai, 2011). Users (or patients) with severe depression status obtain considerable benefits from digital technology usage (Houston, Cooper, & Ford, 2002). Thereby, we propose that the negatively moderate effect of digital technology usage may be strengthened among subgroups with severe depression status of older adults. Thus, we hypothesize the following:

H4: The moderating effect of digital technology usage is strengthened among higher quantile-level subgroups.

Methodology

Data description

The China Health and Retirement Longitudinal Study (CHARLS) is a nationally representative longitudinal survey of persons aged 45 years or older in China. The survey is conducted by the National School of Development of Peking University. The baseline wave of CHARLS conducted in 2011 covered about 10000 households and 17500 individuals in 150 counties and 450 villages. CHARLS respondents are followed up every 2 years by face-to-face computer-assisted personal interview. (Zhao, Hu, Smith, Strauss, & Yang, 2014). Our data are obtained from the harmonized CHARLS and 2015 follow-up.

Measures

The primary independent variable of interest is socioeconomic status of respondents and usage of digital technology. Parental education and self-rated health status during childhood before age 16 (SRH-16) to determine the effect of childhood conditions. In this study, educational level is categorized into two groups: coded 0 for illiteracy indicating no formal education and no ability to read and write, and coded 1 for literacy, which consistent with any of the following: less than lower secondary, upper secondary, or tertiary. SRH-16 is a subjective measure of one's health status before 16 years old and is reported on a five-point scale, ranging from 1 to 5 as follows: poor, fair, good, very good, and excellent. Income includes individual wages and bonus income from work, individual's after tax net income earned from self-employed activity, pension income, and other income from child support or alimony or fringe benefits provided by the work place. Hukou is categorized into two groups: coded 0 for agricultural hukou (rural residence) and 1 nonagricultural hukou (urban residence). For

variables with hyperdispersion property such as income, we take logarithm transformation. Besides, it is worth noting that the proportion of mothers educated is too low (less than 15%) and fathers educated is 44.1%, so we included father's education in the main model. The results of main model included mother's education see Additional file - Table 1.

Access to digital technology is measured by Internet usage and mobile phone ownership. Our research design considers the possible reverse causality. Independent variables, including Internet usage and phone ownership, and dependent variables from our dataset have a natural chronological order. To build our Internet usage variable, we focus on responses in the survey (yes/no) about whether the respondents have accessed the Internet in the past month. To build our mobile phone usage variable, we focus on responses in the survey (yes/no) about whether the respondents own a mobile phone.

Depression status is a dependent variable that is measured by a 10-item CES-D. This measure is used in elderly population (Jadhav & Weir, 2018; Sun, Guo, Liu, & Gao, 2015). Eight items measure symptoms of depression frequency, and two items measure the positive affect on a four-point scale, ranging from 0 to 3. The score is assigned by totaling all item scores after reversing two items of positive affect to fit the measurement scale model, ranging from 0 to 30. From the sociological perspective of depression and considering the cultural bias in responses to the items in CES-D, the outcome is more suitable to be conceptualized as a continuum consisting of flourishing and languishing than be identified as a certain cutoff point to derive health versus illness from the physical illness model (Horwitz, 2013; Lee et al., 2010). Thus, in this study, CES-D score is considered as a continuous variable. And the higher the score is, the severer the depression.

Our study also includes the following individual demographics as controls: age is a continuous variable, ranging 45 years or older; gender is measured as a dichotomous variable, in which 1 equals male; marital status is a dichotomous measure, coded 1 for married and 0 for others.

Econometric model

Our study consists of two parts: examining the effect of individual SES on depression. Model 1 is specified as

$$Doutcome = \beta_0 + \beta_1 edu_{father} + \beta_2 srh_{childhood} + \beta_3 edu + \beta_4 income$$

$$+ \beta_5 hukou + \beta_{6-8} control\ variables + e$$

where $\beta_1, \beta_2, \beta_3, \beta_4,$ and β_5 determine the effects of SES, father's education, and SRH-16 as childhood conditions as well as education, income, and hukou as "formed" and "interferable" SES.

We use model 2 to investigate the moderating effect of digital technology usage.

$$Doutcome = \beta_0{}' + \beta_1{}' edu_{father} + \beta_2{}' srh_{childhood} + \beta_3{}' edu \times usage_{DT}$$

$$+ \beta_4{}' income \times usage_{DT} + \beta_5{}' hukou \times usage_{DT} + \beta_{6-8}{}' control\ variables + e$$

$usage_{DT}$ include Internet usage and mobile phone usage. $\beta_3{}'$, $\beta_4{}'$ and $\beta_5{}'$ indicate the moderating effect of digital technology usage ($usage_{DT}$) on the relationship between SES and depression, respectively.

Statistical analysis: quantile regression

Ordinary least-squares (OLS) estimation of the mean regression models determine how the conditional mean of Y (CES-D scores) depend on covariate X (independent

variables include individual SES and digital technology usage). Quantile regression, which is not influenced by outliers, can analyze the effect of X across the various distributions of Y and provide a holistic view and robust results by calculating coefficient estimates across the various quantiles of the conditional distribution (Koenker & Hallock, 2001). The quantile regression model is specified as

$$Q_{Y_i}(\tau|x_i) = \alpha(\tau) + \beta(\tau)x_i + \beta'(\tau)x_i \cdot z_i + Q_\tau(u).$$

where Y_i is the CES-D scores of the participants, τ is a specific set of quantile level, x_i is the set of participants' individual SES variables, and z_i is the set of participants' digital technology usage variables. Parameter $\beta(\tau)$ models the direct effect of individual SES on depression, and $\beta'(\tau)$ models the moderating effect of digital technology usage. u represents the random error term. The quantile regression model is estimated using weighted least absolute deviation (WLAD) and performed using R package "quantreg."

Results

Descriptive statistics

Our complete dataset, in which all measured variables are not missing, contains 8853 participants. The descriptive statistics of all variables is provided in Table 1. Figure 1 shows the CES-D score of participants. It displays the depression status (or healthy status) of participants through the CES-D score distribution ranging 0-30 and clarifies the CES-D score corresponding to different quantile levels.

[Insert Table 1]

[Insert Figure 1]

Socioeconomic status and depression

To test the hypotheses of the proposed model, we consider three models: (1) one baseline model, where we evaluate H1 and H2; and (2) two interaction models, where we included the interaction term of individual socioeconomic status and digital technology usage to evaluate H3 and H4. Specifically, we built two interaction models to test the moderating effect of Internet usage and mobile phone usage on the relationship between SES and depression, respectively. We report the result of OLS and median regression to explain the average effect. Further, we report the effect of SES on depression at high quantiles (0.6, 0.7, 0.8, 0.9 quantile level) focusing on subgroups with severe depression status.

Table 2 shows the estimates of model 1 (a baseline model). The individual SES has a significantly negative effect on depression on average, including SRH-16 ($\beta_2 = -0.444, \mathrm{p} < 0.01$), education ($\beta_3 = -0.739, \mathrm{p} < 0.01$), income ($\beta_4 = -0.665, \mathrm{p} < 0.01$), and hukou ($\beta_5 = -0.348, \mathrm{p} < 0.05$). Similarly, the above variables negatively influence depression in median regression model. **H1 is partly supported**. Therefore, we confirm that individual health status during childhood, education, income, and hukou as SES affect later life depression on average. People with disadvantageous SES tend to have bad depression outcome in later life.

At high quantiles, we find that the coefficient of father's education is negative and significant ($\beta_1 = -0.344, \mathrm{p} < 0.05, \mathrm{Q} = 0.6$). The effect of health status during childhood, education, and income showed significantly growing trend at high quantiles. The negative effect of hukou is increased to the highest for 0.7 quantile level ($\beta_5 = -0.505, \mathrm{p} < 0.05, \mathrm{Q} = 0.7$). **H2 is partly supported**. For the subgroups with severe

depression status, we find greater disparity in depression among older adults caused by health status during childhood, education, and income. The quantile regression plot of model 1 see Additional file - Figure 1.

[Insert Table 2]

Moderating effect of digital technology

Table 3 shows the estimation of model 2, which evaluated the interaction effect of SES and Internet usage. On average, the interaction effect of education and Internet usage is not significant. In the median regression model, Internet usage has positive moderating effect on relationship between education and depression ($\beta_3' = -1.460, \mathrm{p} < 0.01, \mathrm{Q} = 0.5$). The interaction effect of income and Internet usage is significantly positive ($\beta_4' = 0.502, \mathrm{p} < 0.05, \mathrm{OLS}$ and $\beta_4' = 0.472, \mathrm{p} < 0.05, \mathrm{Q} = 0.5$). As such, Internet usage will negatively moderate the relationship between income and depression. In the scenario of Internet usage, **H3 is partly supported**. On average, Internet usage can reduce the later life disparity in depression caused by income among older adults as we supposed.

At high quantiles, the interaction effect of education and Internet usage is significantly positive ($\beta_3' = 4.570, \mathrm{p} < 0.01, \mathrm{Q} = 0.8$ and $\beta_3' = 4.640, \mathrm{p} < 0.1, \mathrm{Q} = 0.9$). Hence, Internet usage will negatively moderate the relationship between education and depression. The interaction effect of income and Internet usage remains significant, and the coefficient tends to increase, which indicates the strengthened negative moderation effect of Internet usage on the relationship between income and depression. In the scenario of Internet usage, **H4 is partly supported**. For the subgroups faced with severe depression status, Internet usage can reduce disparity in depression caused by education and income in later life as we supposed.

[Insert Table 3]

The estimation of interaction model 2 see Additional file - Table 2, which evaluates the interaction effect of SES and mobile phone usage. The interaction effect of education and mobile phone usage is significantly negative on average condition and 0.6 quantile level ($\beta_3' = -0.561, \mathrm{p} < 0.1, \mathrm{OLS}$ and $\beta_3' = -0.894, \mathrm{p} < 0.1, \mathrm{Q} = 0.6$). Hence, mobile phone usage will positively moderate the relationship between education and depression. The interaction effect of neither income nor hukou with mobile phone usage is not significant. In the scenario of mobile phone usage, **H3 and H4 are not supported**.

Discussion

Main findings

This study aims to (1) analyze the moderating role of digital technology usage on the relationship between SES and depression; and (2) explore the effect of SES on depression as well as the moderating effect of digital technology at high quantiles. By using the China Health and Retirement Longitudinal Study 2015, our study yields three main findings.

First, SES such as self-rated health status during childhood, education, income, and hukou have negative effects on depression among older adults, and these negative effect have a growing trend at high quantiles. Thus, SES causes disparity in depression among middle-aged and aged individuals and reinforces this disparity under severe depression cases. Previous studies have verified disparity in depression of later life at the average population level (Kendig, Gong, Yiengprugsawan, Silverstein, & Nazroo, 2017; Andrade & Quashie, 2016). We focus on subgroups of severe depression status

and confirm disparity in depression caused by SES is lager for vulnerable groups.

Second, Internet usage can reduce the disparity in depression caused by SES such as income and education especially for severe depression subgroups. Specifically, Internet usage reduces the disparity caused by income on average. In quantile regression models, this moderating effect becomes stronger at higher quantiles. For the disparity in depression caused by education, Internet usage has no significant moderating effect on average. Indeed, Internet usage exacerbates this disparity at low quantiles (i.e., healthy subgroups) but reduces it at high quantiles (i.e., severe depression subgroups), which resulting in the insignificant effect on average. This result exhibits the advantage of quantile regressions over OLS. Previous studies have identified digital technology as a protective factor with the deterioration of depression status (Houston et al., 2002). Our results are consistent with this observation, and provide additional insights on the role of digital technology. Besides the direct protective effect of digital technology on depression, it can also reduce the disparity in depression caused by SES. This moderating effect becomes stronger at higher quantiles. Therefore, digital technologies are promising for controlling depression among older adults.

Finally, mobile phone owning cannot reduce the disparity in depression caused by SES. Although previous studies reported that mobile phone usage can improve health outcomes (Rathbone & Prescott, 2017; Richmond et al., 2015), for the elderly, they may be more likely to hold regular mobile phones like other developing countries (Navabi, Ghaffari, & Jannat-Alipoor, 2016) and are unable to accept intelligent support via mobile phone. Our findings are summarized in Table 4.

[Insert Table 4]

Practical implications

Our research has important implications for practice of health disparity interventions and well-being of elderly.

First, the benefits of digital technology as a support system for reducing health disparity and well-being of older adults are confirmed. However, the penetration rate of information technology in middle-aged and aged individuals needs to be improved, especially for developing countries, such as China. Improving access to digital technology for underserved and underdeveloped areas would potentially yield significant reduction in health disparity.

Second, the value of mobile phone, which has high penetration rate of digital technology to improve health outcome, is not utilized. The proven effectiveness of mobile health in developing health interventions (Beratarrechea et al., 2013; Schlicker, Ebert, Middendorf, Titzler, & Berking, 2018) inspire us to launch large-scale delivery of health services through mobile phone. For example, providing social support for the elderly through low-cost short-message services for provider does not require Internet access and additional application to install for users (Schlicker et al., 2018; Müller, Khoo, & Morris, 2016).

Limitations and future research

Our research has following limitations. First, the dataset used this study is self-reported survey data, which might have measurement bias, especially items such as self-rated health status during childhood. Second, the survey includes two simple questions about digital technology usage, so we could measure only internet usage and mobile phone ownership. In this study, digital technology usage is a measurement of access to digital technology, actually. In other words, the details of digital technology usage such as frequency of use, purpose of use, and whether to use smartphone, are

missing in our research. Future research can explore the mechanisms of digital technology usage impact on depression by obtaining detailed digital technology usage data.

Conclusion

We explain how the individual socioeconomic status of middle-aged and aged individuals influence depression outcome and produce disparity and how digital technology moderates this disparity. The model is tested on cross-section data from the China Health and Retirement Longitudinal Study. We find evidence that individual socioeconomic status contributes to the emergence of later-life depression disparity, and digital technology moderates this connection. The result underscores the importance of social context of disparity in depression and the role of digital technology for improving the well-being of middle-aged and aged individuals.

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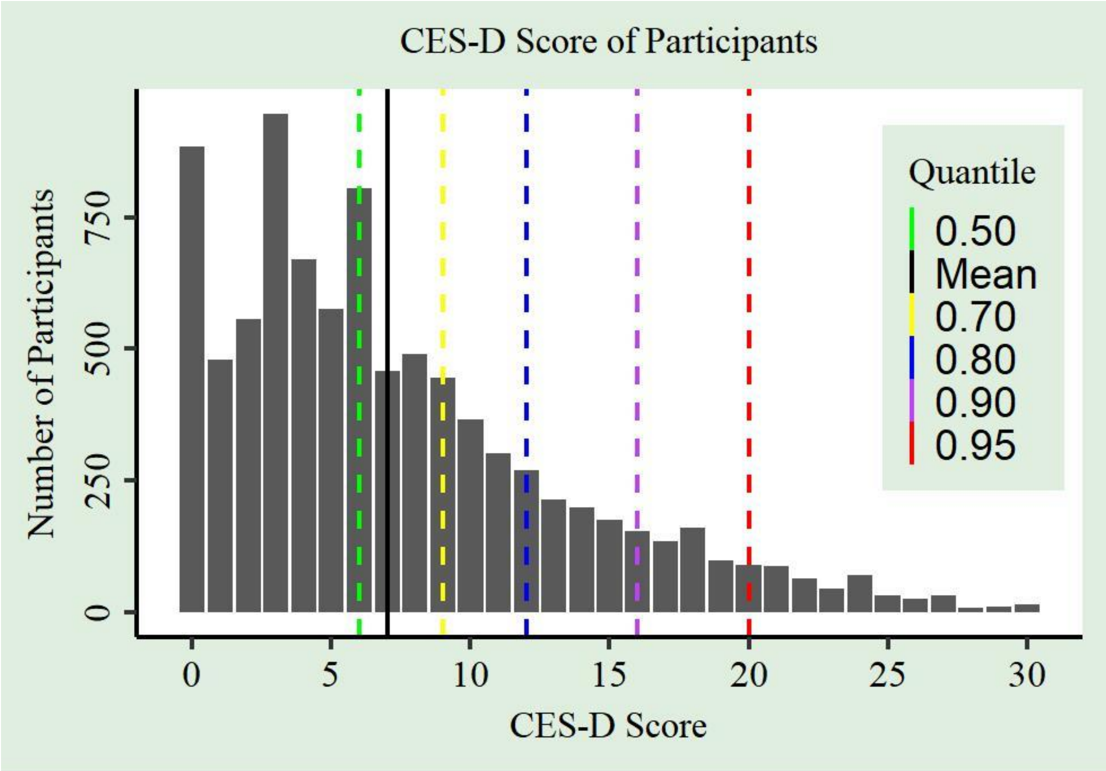
Figures

Figure 1 CES-D score of participants



Note. The figure shows depression status of participants through CES-D score distribution. The x-axis is labeled with the CES-D score. The y-axis refers to the count of participants. The black solid line refers the mean level of CES-D score. The dashed lines refer the different quantile levels of CES-D score, as shown in the legend.

Tables

Table 1 Descriptive statistics

Variables	Frequency	Percent	Mean	SD
Demographics				
Age			60.36	10.27
Gender				
Male	4918	55.5%		
Female	3935	44.5%		
Marital				
Married	7217	81.5%		
Other	1636	18.5%		
Individual Socioeconomic status				
Father's education				
Literacy	3907	44.1%		
Illiteracy	4946	55.9%		
SRH-16				
Poor	535	6.0%		
Fair	1966	22.2%		
Good	1691	19.1%	3.31	1.13
Very good	3546	40.1%		
Excellent	1115	12.6%		
Education				
Literacy	7030	79.4%		
Illiteracy	1823	20.6%		
Income				
Log(income)			8.63	1.74
Hukou				
Agricultural hukou	6604	74.6%		
Non-agricultural hukou	2249	25.4%		
Digital technology usage				
Internet usage				
Yes	880	9.9%		
No	7973	90.1%		
Mobile Phone usage				
Yes	4675	52.8%		
No	4178	47.2%		
Depression status				
CES-D score			7.31	6.10

Table 2 OLS analysis and quantile regression estimation for model 1

Variables	Dependent variable: depression					
	OLS	Quantile regression				
		0.5	0.6	0.7	0.8	0.9
	(1)	(2)	(3)	(4)	(5)	(6)
Individual socioeconomic status						
Father's education	-0.197	-0.181	-0.344**	-0.175	-0.093	-0.098
	(0.132)	(0.145)	(0.170)	(0.194)	(0.243)	(0.294)
SHR-16	-0.444***	-0.460***	-0.486***	-0.521***	-0.649***	-0.676***
	(0.055)	(0.061)	(0.073)	(0.086)	(0.102)	(0.121)
Education	-0.739***	-0.730***	-0.873***	-1.080***	-1.670***	-0.776*
	(0.174)	(0.250)	(0.253)	(0.373)	(0.320)	(0.413)
Income	-0.665***	-0.628***	-0.753***	-0.865***	-1.100***	-1.280***
	(0.046)	(0.055)	(0.060)	(0.075)	(0.090)	(0.106)
Hukou	-0.348**	-0.310*	-0.347*	-0.505**	-0.283	-0.365
	(0.164)	(0.164)	(0.198)	(0.220)	(0.293)	(0.344)
Other						
Age	0.018**	0.011	0.015	0.013	0.017	0.041**
	(0.007)	(0.008)	(0.009)	(0.011)	(0.013)	(0.016)
Gender	-1.330***	-1.290***	-1.400***	-1.980***	-2.230***	-2.660***
	(0.133)	(0.157)	(0.181)	(0.222)	(0.249)	(0.299)
Marital	-1.400***	-1.380***	-1.490***	-1.920***	-2.000***	-2.680***
	(0.161)	(0.218)	(0.235)	(0.308)	(0.294)	(0.409)
Constant	16.100***	15.000***	17.800***	21.600***	26.700***	30.700***
	(0.744)	(0.874)	(0.969)	(1.210)	(1.410)	(1.680)
Observations	8,853	8,853	8,853	8,853	8,853	8,853
R^2	0.110					
Pseudo R^2		0.595	0.596	0.595	0.606	0.601

Note. [a] standardize coefficients are reported; standard errors in parentheses.
[b] ***p < 0.01, **p < 0.05, *p < 0.1.

Table 3 OLS analysis and quantile regression estimation for model 2 (Internet usage)

Variables	Dependent variable: depression					
	OLS	Quantile regression				
		0.5	0.6	0.7	0.8	0.9
	(1)	(2)	(3)	(4)	(5)	(6)
Individual socioeconomic status						
Father's education	-0.168	-0.163	-0.264	-0.138	-0.118	-0.143
	(0.132)	(0.149)	(0.163)	(0.188)	(0.238)	(0.310)
SRH-16	-0.437***	-0.443***	-0.451***	-0.526***	-0.640***	-0.666***
	(0.055)	(0.062)	(0.070)	(0.083)	(0.099)	(0.128)
Education	-0.734***	-0.722***	-0.874***	-1.120***	-1.660***	-0.803*
	(0.175)	(0.238)	(0.255)	(0.376)	(0.311)	(0.421)
Income	-0.685***	-0.642***	-0.752***	-0.894***	-1.130***	-1.300***
	(0.048)	(0.057)	(0.061)	(0.077)	(0.090)	(0.114)
Hukou	-0.137	-0.154	-0.238	-0.266	-0.082	0.256
	(0.181)	(0.201)	(0.215)	(0.242)	(0.329)	(0.407)
Digital technology usage						
Internet usage	-5.800**	-3.500*	-4.690***	-9.620***	-9.370**	-12.40***
	(2.890)	(2.070)	(1.680)	(2.910)	(4.140)	(3.890)
Other						
Age	0.014*	0.008	0.011	0.009	0.013	0.033*
	(0.007)	(0.008)	(0.009)	(0.011)	(0.013)	(0.017)
Gender	-1.330***	-1.290***	-1.360***	-1.970***	-2.190***	-2.790***
	(0.133)	(0.158)	(0.175)	(0.213)	(0.250)	(0.315)
Marital	-1.410***	-1.400***	-1.610***	-1.970***	-2.050***	-2.520***
	(0.161)	(0.212)	(0.235)	(0.307)	(0.290)	(0.414)
Interaction effect						
Internet usage * education	0.556	-1.460***	-0.142	0.765	4.570***	4.640*
	(2.400)	(0.546)	(0.719)	(1.230)	(1.450)	(2.620)
Internet usage * income	0.502**	0.472**	0.431**	0.816***	0.473	0.824*
	(0.206)	(0.211)	(0.179)	(0.271)	(0.439)	(0.449)
Internet usage * hukou	-0.760*	-0.550	-0.440	-0.369	-1.020	-2.680**
	(0.454)	(0.449)	(0.375)	(0.625)	(0.798)	(1.100)
Constant	16.500***	15.200***	18.000***	22.100***	27.200***	31.200***
	(0.753)	(0.900)	(0.951)	(1.210)	(1.400)	(1.760)
Observations	8,853	8,853	8,853	8,853	8,853	8,853
R^2	0.110					

Pseudo R^2	0.595	0.596	0.595	0.607	0.601

Note. [a] standardize coefficients are reported; standard errors in parentheses.
[b] ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4 Summary of findings

Individual socioeconomic status	Disparity of depression			Digital technology intervention
	Average		Higher	
	Mean	Median	>0.5 quantile	
Father's education	NS	NS	Positive	-
Self-rated health status during childhood	Positive	Positive	Increasing	-
Education	Positive	Positive	Increasing	Strengthen (average) Weaken (higher)
Income	Positive	Positive	Increasing	Weaken
Hukou	Positive	Positive	Positive	NS

Note. a NS: not significant.
b -: irreversible SES variables excluded from the interaction analysis.
c The positive effect means that SES exacerbates health disparity, that is, higher SES leads to lower CES-D scores.
d The increasing effect indicates the trend of SES effect on health disparity.

Additional File

Socioeconomic status and depression

When we replacing variable "father's education" with "mother's education" to indicate parental education, model 1 is specified as

$$Doutcome = \beta_0 + \beta_1 edu_{mother} + \beta_2 srh_{childhood} + \beta_3 edu + \beta_4 income$$

$$+ \beta_5 hukou + \beta_{6-8} control\ variables + e$$

where $\beta_1, \beta_2, \beta_3, \beta_4,$ and β_5 determine the effects of SES.

Table 1. *OLS analysis and quantile regression estimation for model 1*

Variables	Dependent variable: depression					
	OLS	Quantile regression				
		0.5	0.6	0.7	0.8	0.9
	(1)	(2)	(3)	(4)	(5)	(6)
Individual socioeconomic status						
Mother's education	-0.224	-0.234	-0.268	-0.371	-0.406	-0.481
	(0.130)	(0.173)	(0.202)	(0.253)	(0.320)	(0.355)
SHR-16	-0.445***	-0.457***	-0.482***	-0.565***	-0.645***	-0.681***
	(0.055)	(0.062)	(0.072)	(0.086)	(0.102)	(0.128)
Education	-0.845***	-0.814***	-1.010***	-1.290***	-1.860***	-0.934**
	(0.173)	(0.244)	(0.253)	(0.387)	(0.319)	(0.443)
Income	-0.666***	-0.629***	-0.761***	-0.861***	-1.100***	-1.300***
	(0.047)	(0.056)	(0.060)	(0.076)	(0.090)	(0.100)
Hukou	-0.302*	-0.228	-0.269	-0.369*	-0.241	-0.174
	(0.164)	(0.168)	(0.202)	(0.220)	(0.298)	(0.353)
Other						
Age	0.017**	0.008	0.010	0.007	0.012	0.040**
	(0.007)	(0.008)	(0.009)	(0.011)	(0.013)	(0.017)
Gender	-1.290***	-1.230***	-1.310***	-1.950***	-2.180***	-2.650***
	(0.133)	(0.155)	(0.181)	(0.221)	(0.248)	(0.310)
Marital	-1.400***	-1.340***	-1.530***	-1.860***	-1.970***	-2.620***
	(0.162)	(0.218)	(0.238)	(0.318)	(0.287)	(0.421)
Constant	16.100***	15.100***	18.100***	22.100***	27.100***	31.000***

	(0.746)	(0.886)	(0.979)	(1.210)	(1.420)	(1.660)
Observations	8,821	8,821	8,821	8,821	8,821	8,821
R^2	0.110					
Pseudo R^2		0.597	0.598	0.596	0.610	0.604

Note. [a] standardize coefficients are reported; standard errors in parentheses.
[b] ***p < 0.01, **p < 0.05, *p < 0.1.

Moderating effect of digital technology

We use model 2 to investigate the moderating effect of digital technology usage including Internet usage and mobile phone usage, respectively. Table 2 shows the estimation of interaction effect of SES and mobile phone usage.

Table 2. *OLS analysis and quantile regression estimation for model 2 (mobile phone usage)*

Variables	Dependent variable: depression					
	OLS	Quantile regression				
		0.5	0.6	0.7	0.8	0.9
	(1)	(2)	(3)	(4)	(5)	(6)
Individual socioeconomic status						
Father's education	-0.203	-0.260*	-0.388**	-0.180	-0.067	-0.185
	(0.132)	(0.144)	(0.171)	(0.193)	(0.228)	(0.297)
SRH-16	-0.442***	-0.446***	-0.510***	-0.547***	-0.650***	-0.676***
	(0.055)	(0.062)	(0.074)	(0.085)	(0.098)	(0.121)
Education	-0.563**	-0.550*	-0.557	-0.802	-1.290***	-0.846*
	(0.228)	(0.308)*	(0.355)	(0.499)	(0.446)	(0.507)
Income	-0.632***	-0.620***	-0.764***	-0.871***	-1.180***	-1.310***
	(0.064)	(0.076)	(0.086)	(0.111)	(0.125)	(0.144)
Hukou	-0.377	-0.254	-0.206	-0.387	-0.408	-0.109
	(0.239)	(0.227)	(0.279)	(0.319)	(0.400)	(0.523)
Digital technology usage						
Mobile phone usage	1.210*	1.260	1.140	0.764	0.250	0.088
	(0.671)	(0.868)	(0.944)	(1.260)	(1.290)	(1.590)
Other						

Age	0.019***	0.007	0.012	0.017	0.020	0.039**
	(0.007)	(0.008)	(0.009)	(0.011)	(0.013)	(0.016)
Gender	-1.350***	-1.320***	-1.460***	-1.980***	-2.210***	-2.660***
	(0.133)	(0.160)	(0.183)	(0.218)	(0.239)	(0.300)
Marital	-1.280***	-1.300***	-1.400***	-1.820***	-1.920***	-2.610***
	(0.165)	(0.205)	(0.248)	(0.310)	(0.284)	(0.408)
Interaction effect						
Mobile phone usage * education	-0.561*	-0.667	-0.894*	-0.786	-0.908	-0.190
	(0.331)	(0.491)	(0.505)	(0.757)	(0.594)	(0.797)
Phone usage * income	-0.053	-0.030	0.004	0.045	0.106	0.050
	(0.083)	(0.095)	(0.111)	(0.135)	(0.152)	(0.192)
Mobile phone usage * hukou	0.026	-0.136	-0.242	-0.230	0.214	-0.404
	(0.318)	(0.312)	(0.379)	(0.415)	(0.518)	(0.703)
Constant	15.400***	14.700***	17.600***	20.900***	26.500***	30.800***
	(0.839)	(0.992)	(1.140)	(1.420)	(1.560)	(1.940)
Observations	8,853	8,853	8,853	8,853	8,853	8,853
R^2	0.110					
Pseudo R^2		0.595	0.596	0.596	0.610	0.602

Note. [a] standardize coefficients are reported; standard errors in parentheses.
[b] ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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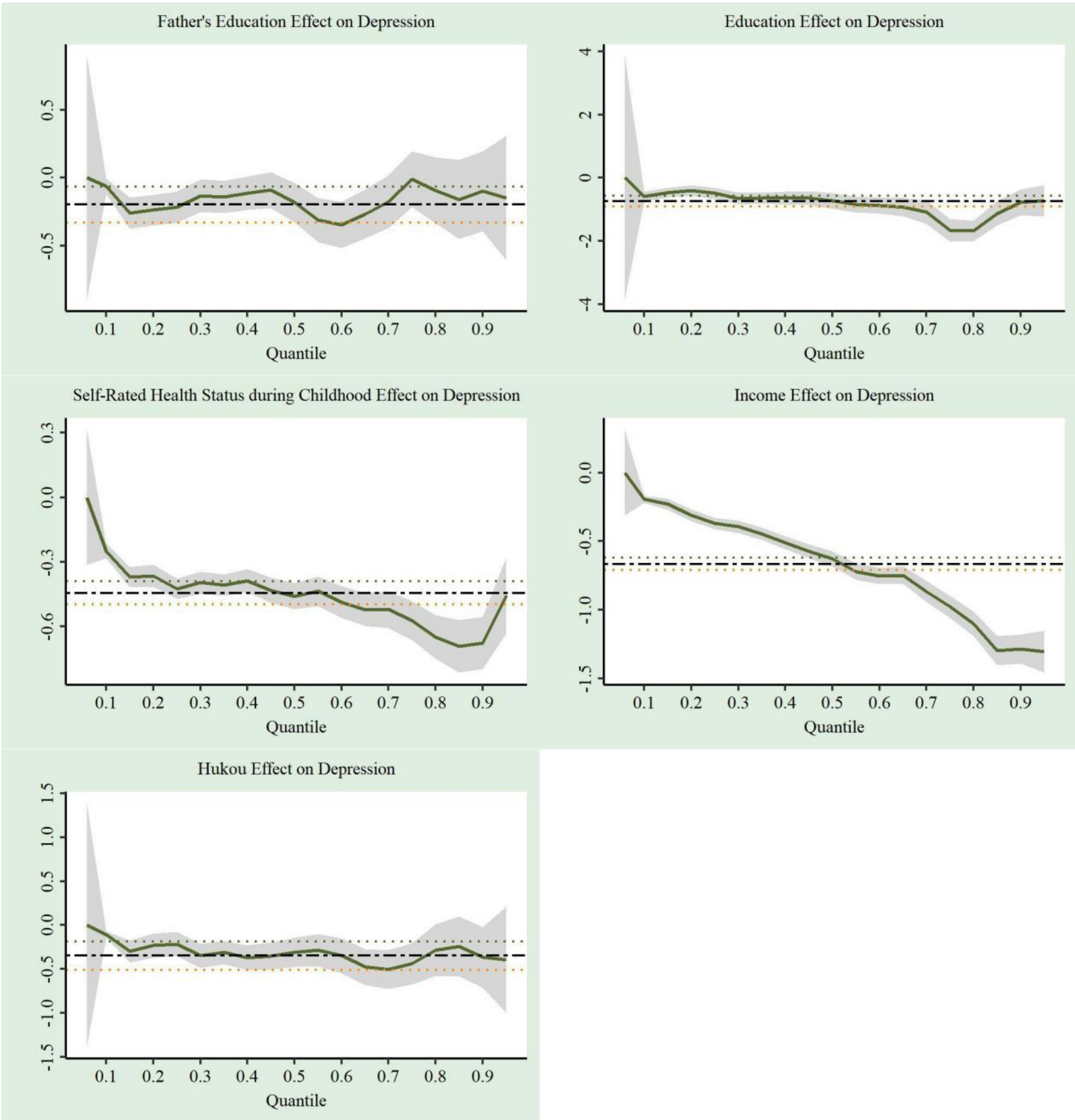
Figure 1. *Effects of individual socioeconomic status on depression in older Chinese adults*



Note. The group shows the effects of individual socioeconomic status measures on depression CES-D score quantiles (green solid line). The x-axis is labeled with the quantile level at which the effects are estimated. The y-axis refers to the effect. The 95% confidence intervals of the effects on quantile are in the shaded area. The black dashed line refers the OLS effect of individual socioeconomic status at the mean CES-D scores.

Figures

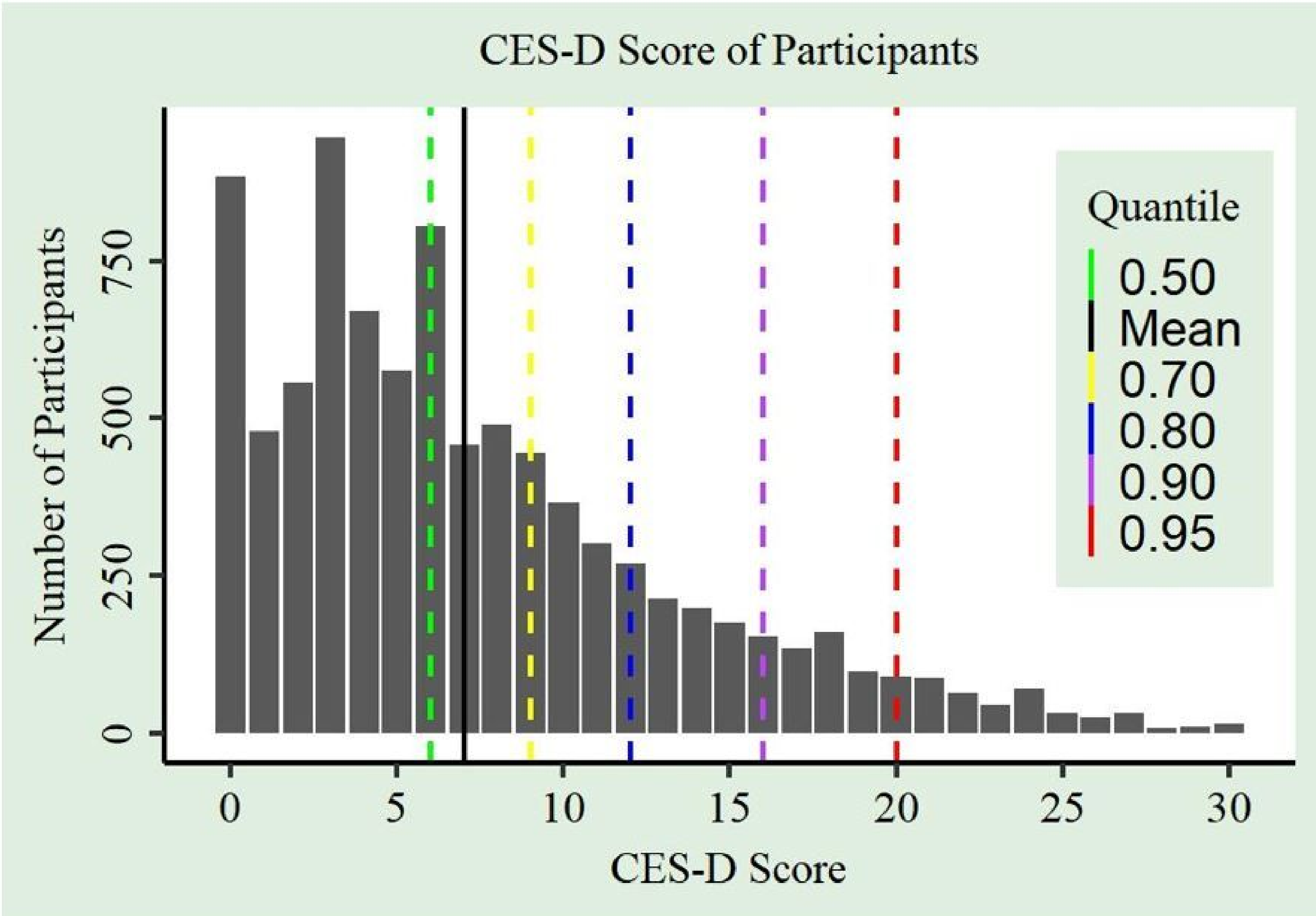


Figure 1

CES-D score of participants Note. The figure shows depression status of participants through CES-D score distribution. The x-axis is labeled with the CES-D score. The y-axis refers to the count of participants. The black solid line refers the mean level of CES-D score. The dashed lines refer the different quantile levels of CES-D score, as shown in the legend.

Supplementary Files

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