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The impact of digital technology on health inequality: evidence from China

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Abstract

Background With the rapid development of digital technology, it is crucial to explore at the individual microlevel whether digital technology can reduce health inequality and discuss potential transmission mechanisms.

Methods This study uses data from the 2020 China Health and Retirement Longitudinal Study (CHARLS 2020) and the ordinary least squares (OLS) method to estimate the impact of digital technology on health inequality. This work then discusses the potential transmission mechanisms through which digital technology influences health inequality. Finally, it analyses the heterogeneity effects of digital technology on health inequality across different groups.

Results We find that digital technology has reduced both physical and mental health inequality. Strengthening family support, enhancing health investment, and improving health behaviours are the transmission paths from digital technology to health inequality. Groups with older cohorts, females, less-educated individuals, low-income individuals, and rural individuals benefit more from physical health inequality, whereas the impact of digital technology on mental health inequality does not differ across groups.

Conclusion Digital technology has a significant impact on reducing both physical and mental health inequality, with particularly notable benefits for vulnerable populations. It is imperative to focus more on the targeted effects of digital technology on these marginalized groups.

Keywords Digital technology, Physical health inequality, Mental health inequality, China

Introduction

Reducing health inequality has long been a primary goal of public health [1]. The rapid advancement of digital technology provides innovative solutions to address health inequality and has garnered significant scholarly interest [2–6]. China, in particular, began its digitalization process in the 1990s. By 2023, the digital economy accounted for 42.8% of China's GDP and contributed 66.45% to GDP growth [7]. Investigating whether China's rapid digitalization has diminished health inequality is valuable for both developing and developed countries. Therefore, we used Chinese micro survey data to examine the relationship between digital technology and health inequality.

Research on the relationship between digital technology and health inequality has produced conflicting findings. One perspective argues that digital technology can positively impact health inequality. Because digital technology is non-rivalrous and nonexcludable [8], the dissemination of health-related information increasingly meets the needs of vulnerable populations, which may help reduce health inequality between various groups [9]. The widespread development of digital technology has bridged the gap between privileged and vulnerable groups in accessing health services and information [10, 11]. Digital platforms are important information carriers

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and can act as buffers against the negative impacts of social and economic factors on health inequality [12]. Furthermore, digital technology has significantly alleviated various factors that severely impact health inequality, including the increase in close and frequent support and care among families [13], increased health investments [14, 15], and improved health behaviours [16, 17]. According to Nie et al., the digital technology brought about by internet use can reduce the significant disparities in mental health between urban and rural residents in China [18]. Oderanti et al. reported that older individuals who use smartphones for social interaction and accessing medical services experience reduced symptoms of depression and loneliness, thereby narrowing the health gap between older people and the general population [19].

Another perspective suggests that digital technology may exacerbate health inequality. The differential adoption rates of digital technology among various demographic groups contribute to inequities in accessing medical services, thereby fostering a siphon effect that further magnifies health inequality [2, 4]. Moro suggested that the high costs associated with digital technology could increase health disparities [20]. Zhang et al. asserted that urban residents are more likely to engage in digitization, thereby potentially improving their health outcomes [6]. Curtis et al. proposed that, owing to the constraints imposed by limited access to digital information resources, rural residents encounter greater difficulties in utilizing telemedicine, thereby widening the health disparity between urban and rural regions [8]. Moreover, misusing digital technology can pose significant health risks. Excessive reliance on digital platforms has been linked to increased instances of anxiety and depression [21, 22], in addition to promoting sedentary lifestyles due to prolonged internet usage, which in turn contributes to health issues such as obesity, heart disease, and diabetes [23]. Consequently, this misuse can further intensify health inequality.

The ambiguous and dual impacts of digital technology highlighted in the literature necessitate a re-examination of its relationship with health inequality at the individual micro level. Therefore, we measure digital technology at the individual level using the 2020 China Health and Retirement Longitudinal Study (CHARLS 2020) and use the frailty index and mental index (measured by the Centre for Epidemiologic Studies Depression Scale) to construct indicators of physical and mental health inequality, discussing whether and how digital technology is related to health inequality in China. We found that digital technology can reduce physical and mental health inequality and that strengthening family support, enhancing health investment, and improving healthier behaviours are potential transmission mechanisms through which digital technology contributes to reducing health inequality. We also found that vulnerable groups benefit more from digital technology in reducing physical health inequality, while there is no significant difference in mental health inequality.

Compared with existing research on the relationship between digital technology and health inequality, our study offers two potential contributions. The first contribution is the extension of the health inequality index. Zhong et al. constructed a health inequality index based on self-rated health [5]. Residents with higher health expectations often overestimate their health, making self-rated health unable to objectively and accurately measure their health status [24]. Scholars often question self-rated health, which lacks horizontal comparability between individuals and regions [25]. Therefore, drawing on studies on frailty indices and mental indices [26, 27], we utilize individual frailty and mental indices to reflect objective health levels and construct a health inequality index. This approach overcomes the subjectivity of self-rated health to build an objective health inequality index.

The second contribution of this study is that it focuses on the impact of digital technology on health inequality at the individual level. Previous studies often included indicators such as regional digitization, digital infrastructure, broadband penetration, and digital economic development as factors of digital technology at the regional level in their models [11, 28, 29]. We focus on the individual level, using whether individuals have internet access to reflect the penetration of digital technology among residents. This approach allows for a more precise identification of the impact of digital technology on health inequality.

Theoretical analysis

It is necessary to explore how digital technology affects health inequality. First, family support theory emphasizes the importance of emotional and material support from children for the physical and mental well-being of the older population [30]. Additionally, digital technology enhances this familial caregiving support. Some studies suggest that family-centred upwards intergenerational support and care help slow cognitive decline in older adults, alleviate symptoms of depression, and enhance their subjective sense of well-being [31, 32]. The literature indicates that support and care by children not only meet the basic needs of older adults but also enhance their social connections and sense of belonging, thereby positively impacting their health and health inequality [33]. The culture of filial piety is particularly important in China, where children are required to play an important role in taking care of their older parents [34]. The development of digital technology has made support and care between families closer and more frequent [13], thereby reducing health inequality.

Second, health capital theory suggests that investing in healthcare and promoting balanced nutrition can improve overall health quality [35]. Digital technology has promoted an increase in health investment. On the one hand, the development of digital technology increases income, providing residents with greater possibilities for consuming fitness exercises, equipment, and health products [15]. On the other hand, digital finance promotes mobile payments, alleviating liquidity constraints and improving residents' consumption preferences, thus expanding their access to health products [36]. Digital tools such as WeChat and Alipay provide residents with access to medical services and facilities [3]. Mobile money transfer (MMT) technology makes it easier for financially underserved households to access informal loans, increasing their utilization of formal healthcare services and reducing health inequality [14].

Finally, the theory of planned behaviour emphasizes the role of individual behavioural intentions in the choice of personal health lifestyles [37]. Digital technology enables people to access more information and enhance their sense of self-efficacy, thereby forming healthy behavioural intentions, improving health behaviours, and enhancing health status [38, 39]. Some studies also suggest that health behaviour affects health and health inequality [40, 41]. For example, long-term smoking, drinking, and other unhealthy habits increase the risk of disease and other physical problems [42]. The development of digital technology disseminates more health knowledge to residents through the internet, promoting more exercise, less alcohol consumption, and smoking reduction [16, 17]. Digital technology enables people to conveniently access medical information and practical tools for daily health management [43]. This facilitates increased participation in health-related activities, enhances overall health-related behaviours, and reduces health inequality [44].

Some studies indicate that an individual's subjective health and mental well-being are negatively correlated with internet addiction and excessive social media dependence [45] and that excessive internet use may lead to increased impulsivity, depression, and anxiety [21, 22]. However, we focus on how digital technology has lessened health inequality, although the effects are not necessarily uniform across different demographics. Based on the above analysis, the potential transmission pathway from digital technology to health inequality involves enhancing individual social participation [46], encouraging individuals to focus on health maintenance and well-being promotion [47], assisting in the acquisition of health knowledge and adopting healthier lifestyles [38, 39]. The theoretical analysis framework is shown in Fig. 1.

Data and methods

Data sources

The data used in this study were obtained by integrating microlevel data from the 2020 China Health and Retirement Longitudinal Study (CHARLS 2020) and city-level data from the "*China City Statistical Yearbook 2021*". CHARLS 2020 covers 150 counties, 450 villages, and 12,000 households in 28 regions of China (excluding Tibet, Ningxia, and Hainan), encompassing 19,000 respondents. This survey focuses on collecting information related to the demographic, physical, and mental health of Chinese residents aged 45 years and above. The city-level data primarily includes metrics such as per capita GDP, population density, and the number of (assistant) physicians.

According to the availability of city-level data, the study selected data from 23 regions and 109 cities from the CHARLS 2020 to match variables such as per capita GDP, population density, and the number of (assistant) physicians. We dropped the observation if one of the variables was missing, ultimately obtaining 15,467 valid observations.

Variables

Health inequality

Research on health indicators has focused primarily on constructing indicators related to physical and mental health, including self-rated health, height/weight, BMI,

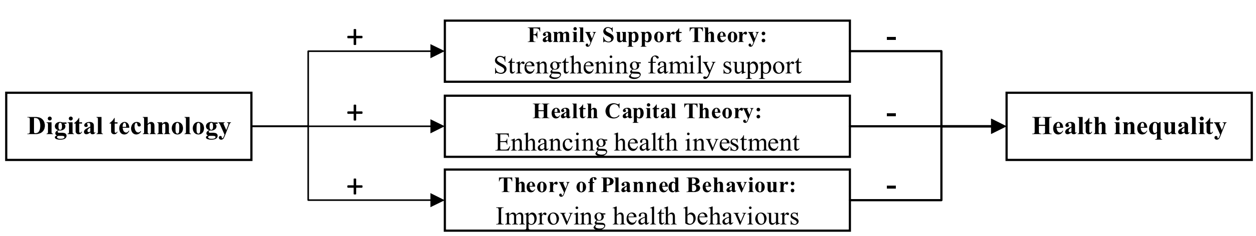

Fig. 1 Transmission pathway from digital technology to health inequality

chronic diseases, and mental health [48–52]. To analyse the impact of digital technology on health inequality, we also select physical and mental health as two dimensions to construct health inequality indicators.

(1) Physical health inequality (PH_I). The frailty index is a comprehensive indicator measuring an individual's health, generally representing the proportion of healthy indicators among all health measurements [53]. It surpasses the limitations of single health indicators such as self-rated health and BMI, effectively reflecting an individual's overall health status. Its validity in reflecting health changes, public health management, and interventions has been widely recognized [26, 54]. The frailty index is defined by multiple variables related to clinical examination and medical history, primarily including cognitive function, ability to perform daily activities, and disease status. We utilize 28 relevant questions on physical health from the CHARLS 2020 questionnaire to calculate the physical frailty index (specific questions and assignments, as shown in Appendix A). The frailty index includes 13 indicators from the Mini-Mental State Examination (MMSE), 6 indicators from activities of daily living (ADL), 6 indicators from instrumental activities of daily living (IADL), and 3 indicators of chronic diseases. The individual frailty index is obtained by dividing the total score of all indicators by the theoretical maximum score of 28, with a range of 0–1. Notably, a higher score on the frailty index indicates better physical health.

In accordance with the literature [5, 29], we use relative health deprivation as an indicator of health inequality. Composite measures, such as the Gini coefficient or Theil index, may not reveal individuals' relative health levels. The core process of relative inequality or deprivation is social comparison, which includes horizontal comparisons between individuals or groups and a reference group, vertical comparisons between value expectations and value capabilities, and temporal comparisons between current and past or future situations [55]. Therefore, health inequality measurement should shift from the aggregate to the micro level to derive credible conclusions [56]. The calculation of relative health deprivation is based on the Kakwani index [55]. Suppose that there are n individuals in group X with similar characteristics (such as age, gender and city). These individuals are ordered in ascending order according to their frailty index within each group. We thus have $X(x_1, x_2, \ldots, x_n)$ where $x_1 \leq x_2 \leq \cdots \leq x_n$, this allows for comparing each person's health status relative to others in determining their degree of relative deprivation.

Specifically, to calculate the relative physical health deprivation of individual i compared with that of individual j, we can assess their health conditions.

$$PH\_I(x_j, x_i) = \begin{cases} x_j - x_i, if x_j > x_i \\ 0, if x_j < x_i \end{cases} \tag{1}$$

Then, when the frailty indices of individuals i are compared with those of all other individuals within the group, we determine their average degree of relative physical health deprivation. The average degree of relative physical health deprivation for individual i is denoted as:

$$PH\_I(x_i) = \frac{1}{n\mu_x}\left(n_{x_i}^{+}\mu_{x_i}^{+} - n_{x_i}^{+}x_i\right) = \frac{1}{\mu_x}\gamma_{x_i}^{+}(\mu_{x_i}^{+} - x_i) \tag{2}$$

Where μ_x is the average frailty index of all individuals within the group, $n_{x_i}^{+}$ is the number of individuals whose health condition is better than that of individual i, $\mu_{x_i}^{+}$ is the average health condition of these $n_{x_i}^{+}$ individuals, and $\gamma_{x_i}^{+}$ is the percentage of individuals whose health condition exceeds that of individual i. Finally, $PH\_I(x_i)$ is the physical health deprivation index of individuals and ranges from 0 to 1, where higher values indicate greater physical health inequality.

(2) Mental health inequality (MH_I). Mental health inequality is another critical component of individual health. Depression disorders have become the second leading cause of healthy life loss due to disability in China [57]. Following the approach of Singhal [58], we refer to the Center for Epidemiologic Studies Depression (CES-D) scale used by the survey centre and select 10 relevant questions from the CHARLS 2020 to calculate the mental index (specific questions and assignments, as shown in Appendix B). The mental index includes 8 indicators from the negative mental index and 2 indicators from the positive mental index. The individual mental index is obtained by dividing the total score of all indicators by the theoretical maximum score of 10, with a range of 0–1. Notably, higher values indicate better mental health. Similarly, using the deprivation indices of Eq. (1) and (2), we compute mental health inequality (MH_I), which ranges from 0 to 1. A higher score indicates greater levels of mental health inequality.

Digital technology

Digital technology ($digit$) is the core explanatory variable in this study. Given the significant role of internet platforms and media in modern society, we use residents' internet usage habits as indicators of their digital technology application capability. We specifically use the

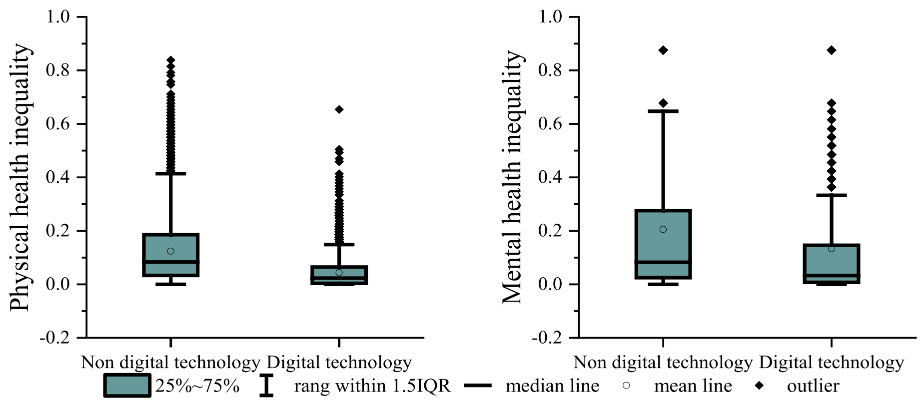

Fig. 2 Box plot of digital technology and health inequality. Note: The median inequality indices for physical health, with nonusers and users of digital technology, are 0.084 and 0.023, respectively. For mental health inequality, the median inequality indices for nonusers and users of digital technology are 0.083 and 0.033, respectively. This finding also indicates that individuals who use digital technology have lower health inequality indices than those who do not

answer to the question "Have you been online in the past month?" in CHARLS 2020 as an indicator of whether residents are using digital technology. Respondents who answer "yes" are assigned a value of 1, whereas those who answer "no" are assigned a value of 0. The indicator of digital technology (*digit*) is a binary variable.

Figure 2 depicts the box plots of digital technology and health inequality. The left plot shows the relationship between digital technology usage and physical health inequality, with mean inequality indices of 0.124 for nonusers and 0.044 for users of digital technology. The right plot illustrates the relationship between digital technology usage and mental health inequality, with mean inequality indices of 0.205 for nonusers and 0.134 for users of digital technology. This finding indicates that individuals who use digital technology experience lower health inequality indices than those who do not, providing anticipated insights and directions for further exploration of the impact of digital technology on individual health inequality.

Covariates

To validate the research hypotheses presented in this paper, it is necessary to control for other factors influencing health inequality. Studies have shown that with age, residents' physical health tends to deteriorate [59]. Factors such as gender, level of education, income,[1] marital status, and rural–urban differences could also impact residents' health status [60, 61]. Therefore, we select *age*, *gender*, *edu*, *income*, *marriage* and *urbanity* as individual control variables. Additionally, the population size, economic development level, and medical resources at the city level may also indirectly affect the health status of residents [5]. To ensure comprehensive and accurate research, the population density logarithm (*pop_density*), per capita GDP logarithm (*per_gdp*), and the logarithm of the number of physicians (*physicians*) are included as regional characteristic variables in the estimation model. The explanations and descriptive statistics of the variables are shown in Table 1.

Empirical analysis model

To identify the impact of digital technologies on health inequality, we employ ordinary least squares (OLS) to estimate the relationship between digital technology and inequality in individuals' physical and mental health. This method has been widely used in studies on health outcomes [5, 15]. The specific estimation model is shown in Eq. (3).

$$HI_{i,c} = \alpha + \beta \mathrm{digit}_{i,c} + \varphi control_{i,c} + \mu \mathrm{community}_c + \delta age_i + \varepsilon_{i,c} \quad (3)$$

In Eq. (3), $i = (1,2,\ldots,15467)$, and $c = (1,2,\ldots,397)$. $HI_{i,c}$ represents the health inequality for resident i in community c, including physical health inequality (PH_I) and mental health inequality (MH_I). $\mathrm{digit}_{i,c}$ denotes whether resident i in community c uses digital technology and is a binary variable. If someone has used the internet in the past month, assign the value of $\mathrm{digit}_{i,c}$ to 1, otherwise, assign the value to 0. $control_{i,c}$ is the set of covariates in this study, including *age*, *gender*, *education*, *income*, *marriage*, *urbanity*, *pop_density*,

[1] The legal retirement age for males is 60 years old in China, and for females it is 55 years old. Therefore, for female individuals aged 55 and below, monthly income is used as a substitute indicator for income, while for female individuals aged over 55, the monthly pension is used as a substitute indicator. For male individuals aged 60 and below, monthly income is used as a substitute indicator for income, while for male individuals aged over 60, the monthly pension is used as a substitute indicator.

Table 1 Explanation and descriptive statistics of variables

Variable	Explanation	N	Mean	Std. dev
PH_I	Physical Health Inequality	15,467	0.095	0.110
MH_I	Mental Health Inequality	15,467	0.170	0.244
digit	Use digital technology assigned 1; nonuse is assigned 0	15,467	0.360	0.480
age	Individual's age	15,467	61.874	9.875
gender	Males are assigned 1; females assigned 0	15,467	0.472	0.499
edu	Years of education	15,467	3.454	1.906
income	The logarithm of monthly income	15,457	7.282	1.081
marriage	Married is assigned 1; unmarried, divorced and widowed are assigned 0	15,467	0.841	0.366
urbanity	Urban areas are assigned 1; rural areas 0	15,467	0.342	0.474
pop_density	The logarithm of people per square kilometre	15,467	5.944	0.859
per_gdp	The logarithm of per capita GDP	15,467	10.801	0.534
physicians	The logarithm of number of (assistant) physicians	15,467	15.421	0.668

The unit of per capita GDP and monthly income is yuan (RMB), The unit of number of (assistant) physicians is a person

per_gdp and *physicians*. There are significant variations in digital technology usage rates across different communities, which lack a clear pattern, and these rates tend to decline with age (the distributions of digital technology usage rates across different communities and age cohorts are shown in Appendix C). It is necessary to control for community-level and age-level biases in digital technology usage. We include community and age fixed effects in Eq. (3). $community_c$ represents community fixed effects, age_i represents age fixed effects, and $\varepsilon_{i,c}$ is the error term. We focus on the coefficient β. If β is significantly negative, digital technology can significantly reduce health inequality. If it is not significant, it suggests that there is no significant relationship between digital technology and health inequality. However, if β is significantly positive, this implies that digital technology may instead increase health inequality.

Results

Health inequality effects of digital technology

To explore the impact of digital technology on health inequality, we estimate the average effect of digital technology on health inequality via Eq. (3). Table 2 Columns 1–2 present the results without incorporating control variables, whereas Columns 3–4 present the results with control variables included. We found that regardless of whether control variables were included, the estimated coefficients and statistical significance of the impact of digital technology on physical and mental health inequality were largely consistent, this indicates the effectiveness of the control variables employed in the study. This consistency across estimates with and without control variables strengthens the robustness of the findings.

Table 2 The impact of digital technology on health inequality

	(1)	**(2)**	**(3)**	**(4)**
	PH_I	*MH_I*	*PH_I*	*MH_I*
digit	−0.048***	−0.056***	−0.026***	−0.046***
	(0.002)	(0.004)	(0.002)	(0.005)
age			0.001***	0.013***
			(0.000)	(0.001)
gender			−0.019***	−0.016***
			(0.002)	(0.004)
edu			−0.017***	−0.010***
			(0.001)	(0.001)
income			−0.001	0.003
			(0.001)	(0.002)
marriage			−0.009***	−0.030***
			(0.003)	(0.006)
urbanity			−0.004	0.026***
			(0.002)	(0.007)
pop_density			−0.095***	−0.034
			(0.029)	(0.111)
per_gdp			0.629***	0.218
			(0.227)	(0.826)
physicians			−0.548***	−0.184
			(0.200)	(0.717)
Constant	0.115***	0.214***	2.240***	0.336
	(0.015)	(0.041)	(0.771)	(2.671)
Community fixed effect	Y	Y	Y	Y
Age fixed effect	Y	Y	Y	Y
N	15,467	15,467	15,457	15,457
R^2	0.235	0.122	0.312	0.131

(1) The robust standard error of clustering to individual level is indicated in parentheses

(2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Based on the estimates with control variables included, as reported Column 3, the coefficient estimating the effect of digital technology on physical health inequality is −0.026 and statistically significant at the 1% level. This suggests that, relative to those who do not use digital technology, digital technology users exhibit reduced physical health inequality of 0.026 units. Column 4 shows that the estimated coefficient for the impact of digital technology on mental health inequality is −0.046 and statistically significant at the 1% level. This finding indicates that digital technology users exhibit a reduction of 0.046 units in mental health inequality compared with those who do not use digital technology. The estimates suggest that digital technology has a significantly negative effect on health inequality, with digital technology significantly reducing individual health inequality.

Additionally, we disaggregate health inequality into subdimensions such as MMSE scores, IADL scores, chronic conditions for physical health, and positive mental expectations and negative mental expectations for mental health. The health inequality indices for each dimension, such as *MMSE_I*, *IADL_I*, and *chronic_I* for MMSE, IADL, and chronic disease inequality, and *PMH_I* and *NMH_I* for positive mental health inequality and negative mental health inequality, are calculated. We employ Eq. (3) to estimate the effect of digital technology on health inequality across different subdimensions, and the findings are presented in Fig. 3. We have observed that digital technology notably curbs inequality in MMSE, ADL, and IADL measures, while it has a potential negative impact on chronic disease inequality, and it is statistically insignificant. Our findings also indicate that digital technology significantly diminishes inequality in both positive and negative mental expectations. These results collectively affirm the robustness of our baseline estimates, highlighting the pivotal role that digital technology plays in mitigating health disparities across diverse dimensions.

Robustness test

Replacing digital techniques

CHARLS 2020 also investigated three questions about the specific use of digital technology, which are "whether to use payments with mobile phones such as Alipay and WeChat payments", "whether to use WeChat", and "whether to use WeChat Moments". Based on the above three questions, we create a binary variable, *digit_exposure*, which captures the exposure to digital technology as an alternative measure. The variable *digit_exposure* is set to a value of 1 if the respondent answers yes to any of the above and 0 otherwise. We then employ Eq. (3) to estimate the influence of exposure to digital technology on health inequality, and the results are shown in Table 3 Columns 1–2. The estimated coefficient for the effect of digital technology on physical health inequality is −0.027 and significantly negative at the 1% level. The estimated coefficient for the effect of digital technology on mental health inequality is −0.048 and significantly negative at the 1% level. The results demonstrate consistency with the estimation coefficients and significance found in the baseline estimation results, reinforcing the robustness of the estimates in this study.

Replacing health inequality

Drawing on the literature [5], we further adapted a method to construct a health inequality index using individuals' self- rated health status from the survey question, "How do you rate your current health status?" This resulted in self- rated health inequality (*SH_I*), which was used as a new dependent variable to reassess the impact of digital technology on health inequality, as shown in Table 3, Column 3. We find that the estimated coefficient for digital technology on *SH_I* is −0.008 and significantly

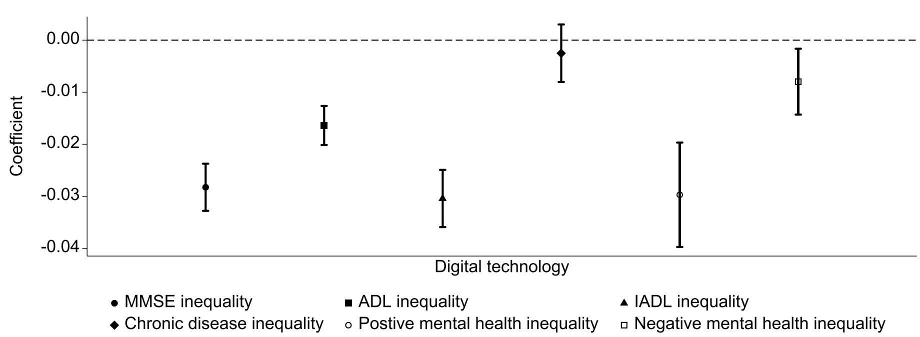

Fig. 3 The impact of digital technology on health inequality in subdimensions. Notes: (1) Each estimate incorporates community and age fixed effects and controls for covariates. The covariates include *age*, *gender*, *education*, *income*, *marriage*, *urbanity*, *pop_density*, *per_gdp* and *physicians*. (2) The vertical line passing through the estimated coefficient is the 95% confidence interval

Table 3 Result of robustness test

	(1) *PH_I*	(2) *MH_I*	(3) *SH_I*	(4) *PH_I_Y*	(5) *MH_I_Y*	(6) *PH_I*	(7) *MH_I*
digjt_exposure	−0.027***	−0.048***					
	(0.002)	(0.005)					
digit			−0.008**	−0.021***	−0.033***	−0.109*	−0.463***
			(0.004)	(0.001)	(0.003)	(0.057)	(0.159)
Controls	Y	Y	Y	Y	Y	Y	Y
Community fixed effect	Y	Y	Y	Y	Y	Y	Y
Age fixed effect	Y	Y	Y	Y	Y	Y	Y
N	15,457	15,457	15,457	15,457	15,457	15,457	15,457
R^2	0.313	0.132	0.083	0.312	0.131		

(1) The robust standard error of clustering to individual level is indicated in parentheses

(2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

(3) Controls include *age*, *gender*, *education*, *income*, *marriage*, *urbanity*, *pop_density*, *per_gdp* and *physicians*

(4) Columns 6–7 present the IV estimation results. In the first stage estimation, the coefficient of the instrumental variables on the endogenous variable is 0.015***, with a robust standard error of 0.003. The Kleibergen–Paap rk LM statistic for the test of IV under-identification is 29.718, and the Kleibergen–Paap rk Wald F statistic for the weak IV test is 29.062

negative. This finding indicates that digital technology significantly reduces self- rated health inequality.

The Yitzhaki index is also used to measure individual inequality [56, 62]. We constructed the Yitzhaki index separately for physical health inequality (PH_I_Y) and mental health inequality (MH_I_Y). We then replace the Kakwani index with the Yitzhaki index and estimate the impact of digital technology on health inequality via Eq. (3). The estimation results are shown in Table 3 Columns 4–5. We find that the estimated coefficients for digital technology on PH_I_Y and MH_I_Y are −0.021 and −0.033, respectively, and both are significantly negative. These findings indicate that digital technology significantly reduces physical and mental health inequality. Therefore, by replacing different explanatory variables and changing the measurement method of health inequality, it was confirmed that the baseline estimate is robust.

IV estimation

Given that the use of digital technology is self- rated by individuals, we employ instrumental variable (IV) estimation to address the potential endogeneity issue arising from measurement bias in digital technology. Specifically, the Broadband China policy[2] is exogenous [29]. The policy is designed to improve broadband network coverage and internet speeds, exhibiting a strong positive correlation with residents' use of digital technology. Moreover, as a city-level policy, it is unlikely to have a direct effect on individual health outcomes. To measure digital technology more precisely at the individual level, we construct a Bartik IV by interacting the Broadband China policy with individual communication fees.[3] Owing to the exogeneity of the Broadband China policy, the Bartik IV satisfies both the relevance and exogeneity conditions. By using the two-stage least squares (2SLS) method, we can derive more accurate estimates of the impact of digital technology on health inequality.

The IV estimation results are presented in Table 3 Columns 6–7. The Kleibergen–Paap rk LM statistic for the test of IV under-identification is 29.718, and the Kleibergen–Paap rk Wald F statistic for the weak IV test is 29.062. Both statistics significantly exceed the critical value of 16.38, confirming the efficacy of the instrumental variables selected in this study. Additionally, the estimated coefficients of *digit* on both physical and mental health inequality are significantly negative and surpass the baseline estimation results, implying that the baseline estimation underestimates the mitigating effect of digital technology on health inequality. Following the resolution of the endogeneity issue related to measurement error, our baseline estimation results remain robust.

Mechanism test

Digital technology may impact health inequality through various mechanisms. Following the theoretical analysis in this study, we primarily validate the support mechanism,

[2] The list of pilot cities for the Broadband China policy was derived from the 2013 and 2014 Broadband China pilot lists published by the Ministry of Industry and Information Technology of the People's Republic of China and the National Development and Reform Commission of the People's Republic of China. We matched 43 Broadband China pilot cities and 66 nonpilot cities in the CHARLS 2020.

[3] The communication fees data comes from the answer of "The expenses for postal and communication services in the past month" in CHARLS 2020.

health investment mechanism, and health behaviour mechanism through which digital technology affects health inequality. First, digital technology makes support and care by children more convenient, which can meet the basic needs of older adults and enhance their social connections and sense of belonging [33]. Therefore, we consider the frequency of contact between individuals and their children (*support*) as an alternative variable for the support mechanism. We use the OLS model for estimation, and the estimation results of the support mechanism are shown in Table 4, Column 1, indicating that digital technology significantly increased the frequency of older adults being supported and cared for by their children, lowering health inequality.

The increase in health investment has improved overall health levels and reduced health inequality [5]. Digital technology can increase residents' income, enabling them to invest more in their health by purchasing health insurance, services, medical devices, and facilities [15, 63]. Therefore, we use the logarithm of the amount spent on purchasing fitness equipment and health products (*healthinvestment*) as an alternative variable for the health investment mechanism, including expenses for fitness exercises, equipment, health products, etc. We use the OLS model for estimation, and the estimation results of the health investment mechanism are shown in Table 4, Column 2, indicating that digital technology significantly increases the health investment of individuals. The increase in preventive health investments contributes to further increasing overall health status, thereby mitigating health inequality [14, 16]. Digital technology can reduce health inequality by increasing individual health investment.

Health behaviour is a key factor in improving individual health levels and significantly impacts the reduction of health inequality [40, 41]. Therefore, we collect information on individuals' health behaviour, including whether they smoke (*smoke*), drink alcohol (*drink*), and engage in more than 10 min of moderate- to high-intensity physical exercise daily (*active*), as variables for the health behaviour mechanism. Considering that the health behaviour mechanisms—*smoke*, *drink*, and *active*—are binary variables, using the logit model for estimating health behaviour mechanisms is appropriate. The estimation results of the lifestyle mechanism are shown in Columns 3–5 of Table 4. Compared with individuals who do not utilize digital technology, those who are exposed to digital technology are associated with having a lower probability of smoking by 1.9 percentage points, a lower probability of drinking by 2.8 percentage points and an 8.5 percentage point greater likelihood of being active. The results indicate that digital technology significantly reduces smoking and drinking behaviours while increasing the likelihood of engaging in moderate to vigorous physical activity, thereby lowering health inequality through individuals' healthier behaviour. Overall, the results in Table 4 validate the impact of digital technology on health inequality through support, health investment, and health behaviour mechanisms.

Heterogeneity analysis

The impact of digital technology on health inequality may vary significantly across groups. First, as age increases, the use of digital technology involves a steep learning curve and associated costs [64], making it more

Table 4 Results of the mechanism test

	(1) *support*	(2) *healthinvestment*	(3) *smoke*	(4) *drink*	(5) *active*
digit	1.559***	0.181***	−0.171***	−0.177***	0.695***
	(0.147)	(0.035)	(0.061)	(0.051)	(0.070)
Marginal effect of *digit*			−0.019***	−0.028***	0.085***
			(0.007)	(0.008)	(0.008)
Controls	Y	Y	Y	Y	Y
Community fixed effect	Y	Y	Y	Y	Y
Age fixed effect	Y	Y	N	N	N
N	15,457	15,457	15,457	15,457	15,457
R^2	0.260	0.133	0.192	0.178	0.050

(1) The robust standard error of clustering to individual level is indicated in parentheses

(2) *** $p<0.01$, ** $p<0.05$, * $p<0.1$

(3) Controls include *age*, *gender*, *education*, *income*, *marriage*, *urbanity*, *pop_density*, *per_gdp* and *physicians*

(4) In Columns 3–5, serious collinearity was found between the age fixed effects and the control variable *age*, so no age fixed effect

(5) The R^2 in Columns 3–5 is Pseudo R^2

challenging for older cohorts to overcome the barriers to using digital technology. Second, due to gender differences, women typically assume more family caregiving and household responsibilities than men [65], and health disparities between genders are widely prevalent. Third, education level has a lifelong impact on individuals' cognitive abilities and learning capabilities [66]. Individuals with higher education levels generally maintain better cognitive abilities later in life [67] and can adapt more quickly to new technologies, thereby benefiting more effectively from the health impacts of digital technology. Fourth, there is a strong positive correlation between income and health, and individuals with lower income levels often face poorer health conditions [68, 69]. Fifth, owing to factors such as economic development levels, urban areas typically have better digital infrastructure and network coverage, whereas remote rural areas may lack such facilities [70].

To measure the differential impact of digital technology on health inequality across different groups, we constructed interaction terms between digital technology and age, gender, education, income, and urbanity (such as $age * digit$, $gender * digit$, $edu * digit$, $income * digit$, and $urbanity * digit$) and incorporated them into Eq. (3), respectively. We then estimate the heterogeneity of the impact of digital technology on health inequality across age, gender, education, income, and urban–rural areas. Figure 4 shows the heterogeneity in the impact of digital technology on physical health inequality across age, gender, education, income, and urban–rural areas. The estimated coefficient for $age * digit$ is significantly negative, indicating that digital technology more effectively alleviates physical health inequality in older cohorts than in younger cohorts. The estimated coefficients for $gender * digit$, $edu * digit$, $income * digit$, and $urbanity * digit$ are significantly positive, suggesting that digital technology has a greater alleviating effect for women, individuals with lower education levels, those with lower incomes, and rural populations. Thus, digital technology is more beneficial in reducing physical health inequality among vulnerable groups. Figure 5 shows the heterogeneity in the impact of digital technology on mental health inequality across age, gender, education, income, and urban–rural areas. The estimated coefficients for the interaction terms are not significant, indicating that the role of digital technology in reducing mental health inequality does not differ significantly across groups. In other words, digital technology has an equitable impact on reducing mental health inequality.

Discussion and conclusions

There is no consensus in the literature regarding whether digital technology can benefit the health sector. Additionally, some studies did not find evidence that digital technology reduces health inequality [2, 4]. Therefore, we further extended the measurement of health inequality to include objective indicators, with particular emphasis on individual-level applications of digital technology. Our research contributes to the study of the relationship between digital technology and health inequality.

Our study revealed that digital technology generally reduces health inequality in China, primarily by alleviating disparities in physical and mental health. Baseline estimates indicate a significant negative correlation between digital technology and both physical and mental health inequality. With the use of digital technology, residents experience reduced physical and mental health inequality. Support and care by children, health investment, and healthier behaviour are crucial pathways through which digital technology alleviates health inequality. Moreover, digital technology has a more pronounced alleviating effect on physical health inequality among older cohorts, women, individuals with lower education levels, those with lower incomes, and rural populations. However, its ability to mitigate mental health inequality across different groups is not significantly different,

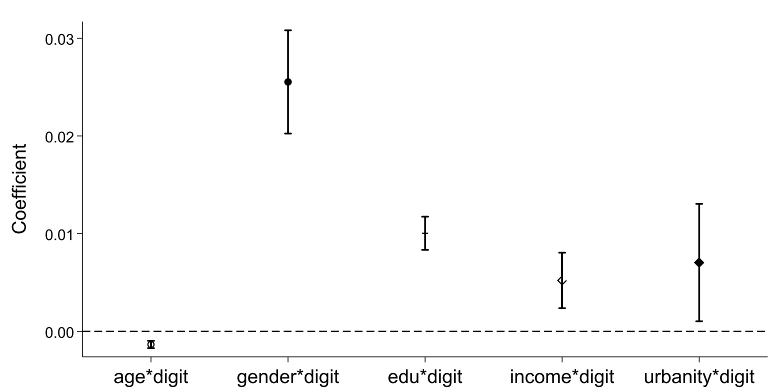

Fig. 4 Heterogeneity for physical health inequality

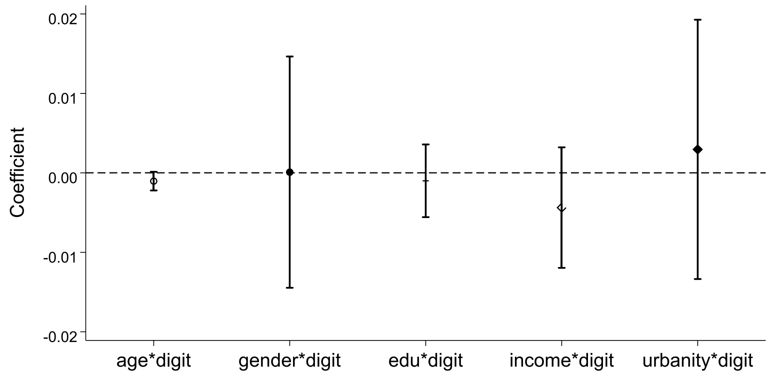

Fig. 5 Heterogeneity for mental health inequality. Notes: (1) Each estimate incorporates community fixed effects and age fixed effects and controls for covariates. The covariates include *age*, *gender*, *education*, *income*, *marriage*, *urbanity*, *pop_density*, *per_gdp* and *physicians*. (2) For gender, males are assigned a value of 1, and females are assigned a value of 0. For urbanity, urban areas are assigned a value of 1, and rural areas are assigned a value of 0. (3) The vertical line passing through the estimated coefficient is the 95% confidence interval

this suggests that digital technology represents a more inclusive and beneficial technological advancement that favours vulnerable groups. Our research provides new policy directions for utilizing digital technology to address health inequality issues effectively.

In this work, our study sample primarily included middle-aged and older individuals aged 45 years and above, who typically require a longer learning process to master digital technology [13]. This demographic often exhibits strong self-control and restraint. Thus, digital technology may have more significant potential in reducing health inequality among them. In contrast, younger individuals have greater proficiency and learning abilities in digital technology, but excessive use may negatively impact health inequality [71]. Therefore, future research needs to explore the impact and mechanisms of digital technology on health inequality across different age groups throughout the entire lifespan more clearly, providing more compelling evidence to support global health initiatives. These findings offer new insights into how digital technology influences health inequality issues. Despite some limitations, they provide valuable references and insights for future policy-making and practices.

The results of this study have several policy implications. First, it emphasizes the importance of digital technology in alleviating health inequality. The findings not only provide insights for China but also serve as a reference for other countries aiming to develop digital infrastructure to improve the health and well-being of their populations. Second, for residents, the use of digital technology to enhance health conditions and reduce health deprivation is beneficial. For example, increasing the frequency of support and care by children, enhancing health investment, improving health behaviours, and accessing health information and services can improve their health and mitigate health inequality. Finally, the impact of digital technology on alleviating health inequality is highly heterogeneous. Appropriate measures should be taken, such as increasing digital technology training services for older, less educated, and low-income populations, increasing attention to women in society, and improving the digital infrastructure in underdeveloped rural areas. These efforts emphasize the role of digital technology in alleviating health inequality among vulnerable groups.

Supplementary Information

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Supplementary Material 1

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Authors' contributions
All authors contributed to this work. Zhang Zhen and Daisheng Tang worked on the study design and method. Zhang Zhen was responsible for manuscript design, data analysis and paper writing while Qiushi Feng supervised analysis again and put forward constructive revised comments on the paper. Xinyuan Wang provided interpretive input and words correcting. All authors critically reviewed and approved the final manuscript.

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Data availability
The research data in this article can be provided by contacting the corresponding author.

Declarations

Ethics approval and consent to participate
The research data used in this paper is sourced from the publicly available database CHARLS 2020. The survey has been approved by the Biomedical Ethics Committee of Peking University. The fieldwork plan for the CHARLS 2020 Household Questionnaire Survey has been approved, with the approval number: IRB00001052-11015. The research data consists of secondary data analysis from which all personal identifiers have been removed. The research methods fully comply with relevant ethical standards and guidelines.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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