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Research Article

Keywords: digital financial inclusion, depressive symptoms, self-reported health, middle-aged and older adults, recentered instrumental variable, hospital resources, telecommunications, China

Posted Date: August 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10797176/v1

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Additional Declarations: The authors declare no competing interests.

Bridging Digital Financial Inclusion and Psychosocial Health: Evaluating the Role of Digital Finance in Enhancing Mental Well-being Across Economic Landscapes

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Abstract

Digital financial inclusion (DFI) may improve access to financial services and information, but its relationship with the psychosocial health of middle-aged and older adults remains insufficiently understood. This study combines the 2011, 2013, 2015, and 2018 waves of the China Health and Retirement Longitudinal Study with city- and provincial-level data on DFI, broadband development, hospital resources, and regional economic conditions. The final dataset contains 78,012 person-year observations from adults aged 45 years and above. Province and year fixed-effects models show that a one-standard-deviation increase in DFI is associated with a 0.271-point reduction in depressive symptoms measured by the CESD score and a 0.033-point reduction in self-reported health scores, where lower scores indicate better health. These relationships remain evident in generalized ordered logit models, propensity-score-weighted estimates, and models with standard errors clustered by respondent. A recentered broadband instrument, constructed from initial broadband exposure and leave-one-out DFI growth, produces estimates close to the baseline results. Formal interaction tests provide limited evidence of consistent differences across broad geographic divisions, although the association varies across economic-hub areas and according to provincial hospital composition. In particular, the negative association is stronger where primary hospitals account for a larger share of hospital resources and weaker where tertiary hospitals are more concentrated. Statistical mediation analysis further identifies significant indirect associations through primary-hospital availability and per-capita telecommunications activity, with the latter accounting for a larger reduction in the DFI coefficient. These findings indicate a stable negative relationship between DFI and poor psychosocial health, while the observational design and identifying assumptions prevent an unconditional causal interpretation.

Keywords: digital financial inclusion; depressive symptoms; self-reported health; middle-aged and older adults; recentered instrumental variable; hospital resources; telecommunications; China

1.Introduction

In recent years, global population ageing has attracted growing international attention. The pace of population ageing today is markedly faster than at any point in history, and this demographic shift

is increasingly moving from developed to developing countries [1]. As one of the world's most populous developing countries, China faces an increasingly severe ageing challenge. According to a bulletin issued by the National Bureau of Statistics of China, the population aged 60 and above reached 323.38 million by the end of 2025, accounting for 23% of the total population, while those aged 65 and above reached 223.65 million, representing 15% of the total population [2]. As the population aging deepens, the mental health of older adults has become a matter of comparable urgency. Late-life depression is one of the most common mood disorders among older adults, with prevalence rising sharply with age — from approximately 5.7% among those aged 60 and above to 27% among those over 85, and reaching as high as 49% among older adults residing in communities or nursing homes — yet these symptoms remain frequently undetected and undertreated [3]. This burden is markedly heavier in developing countries (40.78%) than in developed ones (17.05%) [4].

Among the modifiable risk factors identified for late-life mental health decline, financial insecurity and economic vulnerability stand out as both prevalent and consequential — the WHO explicitly identifies reducing financial insecurity as a first-order strategy for promoting mental health in older age [5]. Within this context, digital financial inclusion (DFI) — as a technology-enabled extension of financial access — has attracted growing empirical attention as a possible channel for improving older adults' psychological well-being. Lei, Shen and Yang [6] find that DFI significantly reduces depressive symptoms and improves self-rated health among China's elderly population, with the effect more pronounced among rural residents. Related evidence on internet use — a closely linked dimension of digital access — points in a similar direction, though the benefits appear conditional: household income amplifies the depression-reducing effect of internet use among older adults [7], while internet use is associated with lower depression risk partly through greater social participation and is moderated by regional informatization development [8].

Nevertheless, this literature offers limited insight into the channel through which DFI improves older adults' mental health, leaving open whether the association reflects a direct economic-buffering effect or operates indirectly through healthcare accessibility and telecommunications infrastructure. Beyond this mechanistic gap, the existing literature presents three further limitations. First, studies addressing the endogeneity of DFI have relied predominantly on binary instruments, which capture only the presence rather than the intensity of digital infrastructure development and are susceptible to weak-instrument bias. Second, heterogeneity analyses have generally relied on subgroup regressions, inferring differential effects from coefficients that vary in magnitude across subsamples rather than from formal interaction tests — leaving unclear whether the reported heterogeneity reflects a genuine effect or sampling variation. Third, medical-resource accessibility — including hospital tier composition and its spatial distribution — has been largely absent from the analytical framework linking DFI to mental health, despite plausibly moderating or transmitting the very relationship under study.

This study examines whether and how digital financial inclusion (DFI) affects the psychological well-being of China's older population, using individual-level data from the 2011, 2013, 2015, and 2018 waves of the China Health and Retirement Longitudinal Study matched with city- and

provincial-level data on broadband penetration, hospital resources, and unemployment. Three findings emerge. First, DFI is associated with significantly lower depressive symptoms and better self-reported health among older adults, a pattern that survives ordered-outcome modeling, propensity-score matching, and instrumentation with a recentered broadband measure addressing weak-instrument concerns. Second, formal interaction tests show that most of the broad geographic heterogeneity implied by earlier subsample comparisons — across eastern/non-eastern, southern/northern, and Yangtze River Economic Belt divisions — is not statistically supported; the association is, however, significantly weaker near the Chengdu–Chongqing Economic Circle than near Shanghai and varies systematically with local hospital composition, weakening where tertiary-hospital resources dominate and strengthening where primary-hospital resources dominate. Third, statistical decomposition indicates that this relationship is partly transmitted through expanded primary-hospital availability and, to a substantially greater extent, through higher per-capita telecommunications activity.

This study makes four contributions. First, it constructs a recentered, continuous broadband-based instrument that captures the intensity rather than the mere presence of digital infrastructure development, addressing the weak-instrument concerns of the binary instruments used in prior work. Second, it replaces subgroup coefficient comparisons with formal interaction tests, showing that most reported regional heterogeneity does not withstand formal testing, while heterogeneity by economic-hub proximity and hospital composition does. Third, it incorporates hospital tier composition into the DFI–mental health framework, a dimension absent from existing studies. Fourth, it provides statistical evidence on the channels underlying this relationship, showing that the association is partly transmitted through primary-hospital availability and, more substantially, through per-capita telecommunications activity.

The remainder of this study is organized as follows. The second part presents a detailed review of the relevant literature. The third part describes the data and variables. The fourth part presents the empirical results. Finally, the study concludes with a summary and policy implications.

2.Literature Review

2.1. Digital Financial Inclusion: Concept, Measurement, and Economic Reach

Digital financial inclusion (DFI) refers to the delivery of payment, credit, insurance, and investment services through mobile and internet-based channels rather than physical financial institutions [9]. Empirically, the concept is most often operationalized through the Peking University Digital Financial Inclusion Index, which draws on Ant Group transaction records to score coverage breadth, usage depth, and digitization degree across China's provinces, prefectures, and counties [10]. An extensive literature has traced this index's reach into household economic life: DFI raises and redistributes household income [11], disproportionately benefits rural households [12], stimulates consumption [13], and expands both insurance purchases [14] and financial-market participation [15]. Health outcomes entered the literature only recently, and largely through a physical rather than psychological lens—older Chinese adults with greater DFI exposure report better physical health [16] and higher household spending on fitness and exercise [17]. Notably, the three sub-dimensions of the index do not contribute equally: coverage breadth,

which essentially records whether a service is locally available, carries little independent weight, while usage depth and digitization degree—measures of how intensively available services are actually used—account for most of the estimated effect [16]. An index that bundles presence with intensity may therefore understate effects concentrated on the intensive margin, a concern that resurfaces later in this review when the identification strategies used to study DFI's mental-health effects are considered.

2.2. Digital Access and the Mental Health of Older Adults

A narrower literature turns this lens toward psychological outcomes among older adults specifically. Using the CHARLS waves employed in this study, Lei, Shen, and Yang report that DFI lowers depressive symptoms and improves self-rated health, with the effect concentrated among rural residents [6]; internet use shows a comparable pattern, amplified by household income [7] and partly channeled through greater social participation [8]. Adjacent outcomes complicate rather than confirm this picture: mobile-payment adoption raises happiness among socially disadvantaged groups in particular [18], digital finance more broadly is tied to higher self-reported happiness [19], and a propensity-score-matched difference-in-differences design links DFI to both health status and social-security participation among the elderly [20]. Depression, examined on its own terms, turns out to be conditional rather than uniform: digital inclusion predicts lower depression scores mainly where noncognitive traits are favorable [21] or cognitive function is relatively intact [22], and the happiness gains attributed to a city-level digital-economy index accrue almost entirely to older adults who are already online [23]—suggesting the psychological payoff from digital access is itself gated by prior digital capability.

Two problems recur across this body of work. Outcome measures shift between depression, self-rated health, life satisfaction, and general happiness—related but distinct constructs—so the direction of a reported effect depends partly on which one a study happened to choose. More consequential for identification, studies that address the endogeneity of digital access typically instrument it with a binary treatment: participation in the Broadband China pilot, or simple internet-access status. Such an instrument records whether infrastructure was present, not how developed it became, which echoes the coverage-versus-intensity distinction already visible in the DFI index itself [16] and leaves the resulting estimates exposed to weak-instrument bias wherever local implementation intensity varied.

2.3. Channels from Digital Finance to Mental Health

Two channels, developed largely in separate literatures, could account for a DFI–depression relationship. The first works through household finances. Grossman's model treats health as a durable stock rather than a good consumed once: it depreciates with age, yields utility directly, and expands the time available for both market and non-market activity, so individuals invest in it up to the point where the marginal return matches the cost of funds [24]. Because that cost falls as income rises and credit becomes cheaper, anything that eases financial constraints should raise health investment—and, insofar as unmanaged material hardship is itself a source of psychological strain, should register in mental as well as physical health. Older adults are

unusually exposed on this margin: they are excluded from traditional credit and insurance markets [25], financial strain is a documented source of psychological distress among the chronically ill [26], and liquidity constraints specifically are known to delay care-seeking [27]. Digital finance, by lowering the cost of credit and payments, is theorized to ease both constraints at once.

The second channel runs through infrastructure and service access rather than household balance sheets, and the evidence for it comes disproportionately from studies built around depression as the outcome. Exploiting the Broadband China pilot as a natural experiment in the same CHARLS panel used here, Zhou, Liang, Yang, Zhou, and Wan find that digital infrastructure reduces depressive symptoms mainly by strengthening old-age services and social well-being rather than income [28]; using the identical policy shock, Li attributes the effect chiefly to strengthened social networks [29]. The pattern recurs outside the CHARLS setting—digital literacy improves mental health partly by expanding social networks [30], and social participation surfaces as an operative pathway alongside cognitive gains in path-analytic work on digital inclusion and depression [22]—which points toward social connectedness, not healthcare utilization narrowly defined, as the operative mechanism within this second channel. Broadband expansion has also been shown to directly reduce the mismatch between medical-resource supply and demand across Chinese cities [31], while network infrastructure raises mental health chiefly by lifting income and consumption, an intermediate case that blurs the boundary between the two channels rather than resolving it [32]; broadband and internet access more generally track older adults' health and well-being in nationally representative panels [33,34].

Taken as a whole, the depression-specific evidence [28,29] tilts toward a social and infrastructural account over the economic-buffering story motivated by [24–27]. But no study estimates both channels within one equation using a continuous measure of infrastructure intensity, so which one carries more weight for depression specifically—as opposed to health or happiness more broadly—remains an open question.

2.4. Spatial and Institutional Sources of Heterogeneity

A separate strand documents how unevenly DFI and China's healthcare system are each distributed across space, though it rarely examines the two together or tests differences formally. The default in DFI heterogeneity work is to split the sample into eastern, central, and western China and compare coefficients across subsamples; one recent study departs from this convention by estimating interaction terms in the pooled sample instead, on the grounds that subsample splits confound genuine heterogeneity with differences in composition and control variables across groups [35]. That correction has yet to be paired with a non-administrative measure of geography.

Growth-pole reasoning offers one such alternative: concentrated investment at a core node radiates outward to surrounding areas, with the strength of the effect declining as distance from the core increases. Applied to China's digital economy directly, central-city digital development has been found to lift peripheral cities' own digital development through income, labor, and capital channels, with the spillover weakening as distance from the center grows [38]. If a comparable radiation pattern holds for DFI's association with mental health, a locality's outcomes should

depend less on which administrative region it falls into than on its proximity to the nearest major digital-economic center—a distinction that east–central–west classifications cannot capture by construction.

On the healthcare side, medical resources track administrative rank rather than population need: residents of higher-tier cities report better subjective physical and mental health, an advantage mediated by the concentration of medical resources there rather than by income or environmental quality [36]. The concentration is sharper still for mental healthcare specifically—China's psychiatric capacity remains clustered in specialty hospitals in major cities, leaving primary-care institutions with little ability to diagnose or treat depression, a gap for which e-health technologies have been proposed, largely on conceptual grounds, as one of few scalable remedies [37]. Consistent with that proposal, broadband expansion has been found to partially substitute for physical hospital capacity by narrowing medical-resource mismatch [31], suggesting the two margins are not independent.

Two gaps follow. The shift toward formal interaction testing [35] has not been paired with a geographic identification strategy built around economic-hub proximity rather than administrative classification, despite a theoretical basis for expecting exactly this kind of distance-decaying effect [38]. And although resource concentration [36] and digital-infrastructure access [31] have each been shown to shape health independently, hospital-tier composition has not been modeled as a moderator of DFI's association with depression, notwithstanding the conceptual case for treating digital infrastructure and hospital capacity as substitutable channels for mental healthcare access [37]. Closing both gaps—replacing subsample comparisons with formal interaction tests, and incorporating hospital-tier composition alongside a continuous measure of digital-infrastructure intensity—motivates the empirical strategy adopted in this study.

3. Data and Model Specification

3.1 Data Description and Sample Construction

The empirical analysis combines individual-level data from the China Health and Retirement Longitudinal Study (CHARLS) with city- and provincial-level information on digital financial inclusion, broadband development, medical resources, and regional economic conditions. CHARLS is designed as a longitudinal survey of middle-aged and older Chinese adults and supplies the demographic, household, and health measures used here [39]. The analysis uses the 2011, 2013, 2015, and 2018 waves. The Peking University Digital Financial Inclusion Index provides the principal explanatory variable [10], while the contextual files provide information on the Broadband China pilot, broadband and Internet penetration, hospital resources, geographic characteristics, and the provincial unemployment rate.

The original CHARLS file was organized in wide format, with wave-specific measures stored separately for each respondent. We standardized the variable names across the four waves and reshaped the file into long format using respondent ID and survey year. This procedure converted 25,586 respondent records into 102,344 potential person-year observations. The reshaped variables included age, marital status, household registration, rural residence, self-reported health, household assets, income and consumption, CESD, and life satisfaction.

Household size was subsequently merged into the person-year dataset using respondent ID and age. Before the merge, 288 duplicate ID-age observations were removed from the household-size file to ensure that each merge key appeared only once. All 102,344 person-year observations were successfully matched to that file. Following the original processing order, an additional 11,956 duplicate ID-age records were removed from the merged individual-level dataset.

The individual records were then linked to the contextual datasets. City and year were used to connect information on the Broadband China pilot, gigabit-broadband policies, and broadband access. Administrative division code and year were used to merge prefecture-level Internet-penetration information. Province and year were used to incorporate data from the China Health Statistics Yearbook, including the numbers of tertiary, secondary, and primary hospitals and the provincial unemployment rate.

Consistent with the study focus on middle-aged and older adults, observations younger than 45 were excluded, removing 2,347 person-year records. We then excluded 481 observations with a recorded birth year after 1973. After these restrictions, the pooled file contained 78,012 person-year observations.

Following the prespecified coding rule, 7,006 missing values in broadband users per 100 permanent residents were replaced with zero. No replacements were required for Internet users per 100 residents because that variable contained no missing observations after linkage. The zero replacement is an explicit construction assumption rather than observed evidence of zero broadband use. If the missing values reflect incomplete reporting, the raw broadband measure may contain measurement error.

3.1.1 Variables and Measurement

Digital financial inclusion was measured at the city-year level and standardized using the prespecified centering and scaling constants. The underlying index summarizes the local development of digital financial services and is available at several geographic levels [10]:

$$DFI_{ct}^{STD} = \frac{DFI_{ct}^{Raw} - 119.7}{78.4} \quad (1)$$

The standardized measure was available for all 78,012 observations. Gender was coded as one for women and zero for men. Rural residence was coded as one for respondents living in a rural village and zero for those living in an urban community. Valid gender information was available for all observations, while valid rural-residence information was available for 69,153 observations. Self-reported health and life satisfaction were converted from labeled source values to numeric scales ranging from 1 to 5. Higher self-reported health scores indicate worse perceived health, whereas higher life-satisfaction scores indicate greater satisfaction. CESD was retained as a continuous score from 0 to 30 and was additionally divided into four ordered categories: 0-9, 10-15, 16-21, and 22-30. These categories represent progressively more severe depressive symptoms. The use of a shortened CES-D measure in older populations is supported by evidence that the shorter forms preserve the principal symptom dimensions with limited loss of precision [40].

The final dataset contained 78,012 potential person-year observations, but estimation samples differed because of item-specific missingness. CESD was available for 60,434 observations, self-reported health for 62,920, life satisfaction for 58,935, age and household size for 66,388, and rural residence for 69,153. The regression models therefore use outcome-specific complete-case samples. Differences across outcomes may partly reflect sample composition, and systematic

missingness could introduce selection bias. To describe the resulting analytical data before proceeding to the regression analysis, Table 1 reports the principal descriptive statistics.

3.2 Descriptive Statistics

Table 1 summarizes the analysis variables after the prespecified restrictions excluding observations younger than 45 and those born after 1973. The descriptive statistics are computed variable by variable; consequently, the number of observations differs because of item-specific missingness.

Table 1. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
CESD score	60,434	8.077	6.230	0	30
Self-reported health	62,920	2.955	0.969	1	5
CESD category	60,434	1.513	0.820	1	4
Digital financial inclusion (standardized)	78,012	0.001	1.000	−1.397	3.688
Age	66,388	60.340	10.078	45	118
Year of birth	78,012	1954.084	10.540	1900	1973
Rural residence	69,153	0.585	0.493	0	1
Female	78,012	0.511	0.500	0	1
Household size	66,388	3.216	1.636	1	16
Survey year	78,012	2014.301	2.602	2011	2018
Broadband China pilot	78,012	0.165	0.371	0	1
Broadband users per 100 residents	78,012	16.863	12.655	0	91.523
Recentered BBU instrument	78,012	1.383	29.158	−139.817	85.088
Tertiary hospitals	78,012	84.780	42.093	18	206
Secondary hospitals	78,012	329.464	118.607	104	629
Primary hospitals	78,012	336.943	257.136	8	1,100
Yangtze River Economic Belt	78,012	0.425	0.494	0	1
Unemployment rate	78,012	3.374	0.495	2.1	4.5

Notes: CESD ranges from 0 to 30, with higher values indicating more depressive symptoms. Self-reported health ranges from 1 to 5, with higher values indicating worse perceived health. CESD category ranges from 1 (least severe) to 4 (most severe). All statistics are calculated from the final analytical dataset.

The pooled dataset contains 78,012 person-year observations before outcome-specific missingness. Mean CESD was 8.077, while mean self-reported health was 2.955. The standardized digital financial inclusion measure had a mean close to zero (0.001) and a standard deviation of 1.000. Rural residence was observed for 69,153 records, of which 58.5% were classified as rural. The differing outcome and covariate sample sizes indicate that the regression samples are complete-case samples for their respective specifications rather than a single common sample.

The table also documents substantial variation in the contextual environment in which respondents lived. Broadband users ranged from 0 to 91.523 per 100 residents, while the counts of tertiary, secondary, and primary hospitals ranged from 18 to 206, 104 to 629, and 8 to 1,100, respectively. This dispersion supplies the cross-area variation used in the subsequent instrumental-variable and

heterogeneity analyses.

The analysis first establishes the adjusted HDFE association, then introduces 2SLS specifications, and finally applies a recentered formula instrument. Each successive specification addresses a distinct identification concern and is evaluated against the preceding estimates rather than treated as an unrelated model [50–53]. The near-zero mean of standardized DFI is a consequence of the specified transformation rather than a substantive threshold, so coefficients are interpreted for a one-standard-deviation increase.

4. Empirical Results

4.1 Baseline Estimates

The baseline specification estimates the adjusted association between city-level digital financial inclusion and the health outcome of individual i, living in city c within province p, in survey year t. Province fixed effects control for time-invariant differences across provinces, while year fixed effects absorb shocks shared across survey years. The individual-level covariates account for observed differences in respondent characteristics:

$$Y_{icpt} = \beta_0 + \beta_1 DFI_{ct} + X'_{it}\gamma + \mu_p + \tau_t + \epsilon_{ict} \quad (2)$$

X includes age, rural residence, gender, and household size; the province and year terms denote the corresponding fixed effects. Columns (3)–(6) implement two-stage least squares (2SLS), which isolates the component of DFI predicted by an excluded instrument [50]. The first stage instruments DFI using either the Broadband China pilot indicator or raw broadband penetration, and the second stage replaces DFI with its instrumented component [42,43,50].

$$\text{First Stage: } DFI_{ct} = \pi_0 + \pi_1 Z_{ct} + X'_{it}\pi + \mu_p + \tau_t + \nu_{icpt} \quad (3)$$

$$\text{Second Stage: } Y_{icpt} = \beta_0 + \beta_1 \widehat{DFI}_{ct} + X'_{it}\gamma + \mu_p + \tau_t + \epsilon_{icpt} \quad (4)$$

Table 2. Main HDFE, Dummy IV, and Raw Broadband IV Estimates

	HDFE: CESD	HDFE: SRH	Pilot IV: CESD	Pilot IV: SRH	Raw BBU IV: CESD	Raw BBU IV: SRH
DFI (standardized)	−0.271***	−0.033***	−1.764***	−0.140***	−4.959***	−0.520***
	(0.066)	*(0.010)*	*(0.308)*	*(0.049)*	*(0.444)*	*(0.068)*
Age	0.044***	0.013***	0.045***	0.013***	0.047***	0.014***
	(0.003)	*(0.000)*	*(0.003)*	*(0.000)*	*(0.003)*	*(0.000)*
Rural	1.643***	0.155***	1.587***	0.151***	1.468***	0.137***
	(0.051)	*(0.008)*	*(0.052)*	*(0.008)*	*(0.055)*	*(0.008)*
Female	2.097***	0.174***	2.102***	0.174***	2.112***	0.175***
	(0.049)	*(0.008)*	*(0.049)*	*(0.008)*	*(0.051)*	*(0.008)*
Household size	−0.116***	−0.002	−0.106***	−0.002	−0.085***	0.001
	(0.016)	*(0.002)*	*(0.016)*	*(0.002)*	*(0.017)*	*(0.002)*
Observations	60,434	62,920	60,434	62,920	60,434	62,920
R^2	0.079	0.057	0.042	0.030	−0.028	−0.003

Notes: All regressions control for year and province fixed effects. Robust standard errors are reported in parentheses. SRH refers to self-reported health, with a higher score indicating poorer health. In columns (3) and (4), the Broadband China pilot is used as the instrument for DFI. Columns (5) and (6) use broadband users per 100 residents as the instrument. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. The negative R^2 values in the IV models are possible in 2SLS estimation

and do not have the same interpretation as the usual R^2 in OLS models.

The fixed effects models show a negative relationship between DFI and both health outcomes. A one standard deviation increase in DFI was related to a 0.271 point decrease in CESD. The standard error was 0.066, and the estimate was significant at the 1 percent level, using 60,434 observations. For self reported health, the estimated decrease was 0.033 points. The standard error was 0.010, and the sample included 62,920 observations. This result was also significant at the 1 percent level. Since higher self reported health scores indicate poorer health, the negative coefficient represents better health.

The instrument estimates had the same negative direction but were much larger. Using the Broadband China pilot as the instrument, a one unit increase in predicted DFI was related to a 1.764 point decrease in CESD and a 0.140 point decrease in self reported health. Their standard errors were 0.308 and 0.049. When the number of broadband users per 100 residents was used as the instrument, the estimated decreases were 4.959 points for CESD and 0.520 points for self reported health. The standard errors were 0.444 and 0.068. All four estimates were significant at the 1 percent level.

The covariate estimates also indicate that the DFI coefficient is obtained after accounting for pronounced observed health gradients. Rural residence and female gender were positively associated with both adverse outcomes, whereas household size was negatively associated with CESD in the baseline model. These coefficients are adjustment parameters rather than the focus of the analysis. Since continuous scores can obscure whether DFI is related differently to mild and severe categories, Table 3 next evaluates the ordered outcomes without imposing a common proportional-odds slope.

4.2 Ordered-Outcome Estimates

To accommodate ordinal outcomes without imposing a single proportional-odds coefficient at every threshold, generalized ordered logit models were estimated [44]. For ordered outcome Y with K categories, the model is

$$\log\left[\frac{\Pr\left(Y_{icpt} > j\right)}{1 - \Pr\left(Y_{icpt} > j\right)}\right] = \alpha_j + \beta_j DFI_{ct} + \mathbf{X}_{it}^{'}\boldsymbol{\gamma}_j, \qquad j = 1, \ldots, K-1$$

$$OR_j = exp\left(\beta_j\right) \tag{5}$$

Exponentiating βj yields a threshold-specific odds ratio. An odds ratio below one indicates lower odds of being above threshold j—that is, of belonging to a worse outcome category—conditional on the included covariates.

Table 3. Generalized Ordered Logit Odds Ratios

	CESD category	Self-reported health
Threshold 1	0.893***	0.775***
	(0.008)	*(0.009)*
Threshold 2	0.893***	0.916***
	(0.011)	*(0.009)*
Threshold 3	0.891***	0.846***
	(0.019)	*(0.008)*
Threshold 4	—	0.871***
		(0.017)

Observations	60,434	62,920

Notes: Reported values are odds ratios for standardized DFI. Models adjust for gender, age, rural residence, and household size and use heteroskedasticity-robust standard errors. CESD has four categories and therefore three cumulative thresholds; self-reported health has five categories and four thresholds. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

For the CESD categories, the odds ratios were very similar across the three thresholds: 0.893, 0.893, and 0.891. This means that a one-standard-deviation increase in DFI was associated with about 10.7%–10.9% lower odds of being classified into a more severe depression category, after controlling for the other variables.

The self-reported health results show more variation across the four thresholds. Because SRH is coded from 1 to 5, a higher category represents poorer perceived health. The first threshold compares respondents in categories 2–5 with those in category 1, while the second compares categories 3–5 with categories 1–2. The remaining thresholds make similar comparisons at higher levels of poor health. All estimated odds ratios were below one and significant at the 1% level, indicating that higher DFI was consistently associated with lower odds of falling into a worse SRH category.

The size of this association, however, differed across the thresholds. The odds ratio at the first threshold was 0.775. Thus, a one-standard-deviation increase in DFI was associated with approximately 22.5% lower odds of reporting any health category worse than category 1, conditional on the covariates. At the second threshold, the odds ratio increased to 0.916, corresponding to an 8.4% reduction in the odds of reporting a category above 2. This was the smallest estimated association among the four thresholds. The other threshold-specific estimates also remained below one, but their magnitudes fell between these two values.

These differences suggest that the relationship between DFI and self-reported health is not equally strong at every point of the SRH distribution. It appears stronger when distinguishing the best health category from all poorer categories, but weaker when comparing respondents across the middle part of the scale. A standard ordered logit model would impose one common odds ratio on all four comparisons and would therefore hide this variation.

Tables 2 and 3 together suggest that the finding does not depend on measuring health only as a continuous variable. Still, these results cannot fully address reverse causality or omitted-variable bias. In Table 2, the instruments constructed from the pilot program and raw broadband data show strong first-stage relevance. The Kleibergen–Paap F statistics for different outcomes range from 1,397.10 to 1,568.54. However, the second-stage coefficients are much larger than those from the baseline HDFE models. The following analysis therefore uses a formula-based instrument that combines predetermined exposure with leave-one-out growth variation [51,52]. Following the design-based method of Borusyak and Hull [49,53], we recenter this instrument and remove its common component for each year. We then examine whether the adjusted estimates are closer to the magnitude and direction of the baseline fixed-effects results.

4.3 Recentered-Instrument Estimates

A common type of formula-based instrument combines predetermined exposure with common shocks. Its identifying assumptions may concern either the initial exposure pattern or the quasi-random assignment of the underlying shocks [51,52]. Borusyak and Hull show that formula-based instruments can still include a systematic component when exposure to otherwise exogenous shocks is not randomly distributed [49]. To address this issue, they propose subtracting

the expected value of the instrument under counterfactual assignments of the shocks. The identifying variation is therefore measured relative to the conditional mean generated by the exposure pattern [49,53]. Based on this approach, we construct an adjusted broadband instrument using province p's broadband penetration rate in 2011 and the leave-one-out growth of national DFI. Let $g_{-p,t}$ denote the leave-one-out mean level of DFI, and define its growth relative to the 2011 baseline as follows:

$$\Delta g_{-p,t} = g_{-p,t} - g_{-p,2011}, \quad (6)$$

Let $\overline{\Delta g_t}$ denote the mean of this growth measure across provinces in year t. For each survey year, we assume that the provincial growth measures are exchangeable across provinces. We use permutations within the same year to define the possible counterfactual assignments of the shocks in the design-based framework [49,53]. Under this assignment rule, the counterfactual mean of the proposed instrument is equal to the predetermined broadband penetration rate multiplied by the mean shock across provinces in the same year. Since the instrument is linear in the shock, taking the average over all permitted assignments gives the following recentered expression:

$$Z_{pt}^{R} = s_{p,2011}\left(\Delta g_{-p,t} - \overline{\Delta g_t}\right). \quad (7)$$

and let $\overline{\Delta g_t}$ denote the cross-province mean of $\Delta g_{-p,t}$. The recentered instrument is constructed as

$$Z_{pt}^{R} = s_{p,2011}\left(\Delta g_{-p,t} - \overline{\Delta g_t}\right).$$

This transformation first removes the component of leave-one-out DFI growth that is common to all provinces in the same year. The remaining variation indicates whether the DFI growth associated with a province is above or below the annual provincial mean. We then multiply this relative growth measure by the broadband penetration rate observed in 2011. Following the recentering method proposed by Borusyak and Hull [49,53], we calculate the expected value of the candidate instrument under the possible reassignment of provincial shocks within each year and subtract this value from the original instrument. The adjusted instrument therefore retains only the variation that differs from the level implied by the general pattern of shock assignment. In the empirical analysis, we begin with the conventional broadband instruments. We then construct an instrument that combines the predetermined broadband penetration rate with leave-one-out national DFI growth and apply the recentering adjustment described above. The equations used to estimate the relationship between the instrument and broadband development, and between predicted broadband development and health outcomes, remain the same as those reported for Table 2. Instrument relevance is assessed using the Kleibergen–Paap statistic, which allows for heteroskedasticity [43]. The Stock–Yogo critical values are also reported for reference, although they were originally derived under the assumption that the errors are independently and identically distributed [42].

Table 4. First- and Second-Stage Estimates Using the Recentered BBU Instrument

	First stage: DFI	Second stage: CESD	Second stage: SRH
Recentered BBU	−0.013***		
	(0.000)		
DFI (standardized)		−0.228**	−0.032**
		(0.102)	*(0.015)*
Age	0.000***	0.044***	0.013***

	(0.000)	*(0.003)*	*(0.000)*
Rural	−0.036***	1.644***	0.155***
	(0.002)	*(0.051)*	*(0.008)*
Female	0.001	2.097***	0.174***
	(0.002)	*(0.049)*	*(0.008)*
Household size	0.001*	−0.116***	−0.002
	(0.001)	*(0.016)*	*(0.002)*
Observations	66,388	60,434	62,920
R^2	0.921	0.050	0.032
Kleibergen–Paap F	—	21,191.61	21,952.17

Notes: All equations include year fixed effects, province fixed effects, and the controls listed in the table. Standard errors allow for heteroskedasticity and are reported in parentheses. The first stage estimation uses observations with complete information for the included covariates. Separate F statistics are reported for the CESD sample and the self reported health sample used in the 2SLS estimation. Each model contains one instrument and one endogenous variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The recentered broadband instrument strongly predicted DFI in the first stage estimation. A one unit increase in the instrument was associated with a 0.013 unit decrease in DFI. The standard error was below 0.001, and the coefficient was significant at the 1 percent level. The Kleibergen–Paap F statistic reached 21,191.61 in the CESD sample and 21,952.17 in the self reported health sample. These values were more than ten times those obtained from the pilot program and unadjusted broadband instruments in Table 2. The original instrument already had strong predictive power. Recentring removes the growth component shared by provinces in the same year and uses the remaining relative variation to identify the effect of DFI. This variation still strongly predicted DFI.

The second stage estimates showed a negative relationship between DFI and both health outcomes. A one unit increase in predicted DFI was associated with a 0.228 point reduction in the CESD score. The standard error was 0.102, and the corresponding p value was 0.025. For self reported health, a one unit increase in predicted DFI was associated with a 0.032 point reduction in the outcome score. The standard error was 0.015, with a p value of 0.032.

The estimates from the recentered instrument were close to the baseline HDFE results. For CESD, a one unit increase in predicted DFI was associated with a 0.228 point reduction in the score, compared with 0.271 points in the baseline model. For self reported health, the estimated reductions were 0.032 and 0.033 points, respectively. The signs, significance levels, and coefficient sizes were similar across the two specifications. The large coefficients obtained from the pilot program and unadjusted broadband instruments in Table 2 were not observed after recentering. This similarity supports the stability of the main result across model specifications.

The recentered specification provides the final IV results. It applies the adjustment proposed by Borusyak and Hull to remove the expected component caused by the nonrandom distribution of broadband exposure [49,53]. The remaining analysis studies whether the relationship between DFI and psychosocial health varies across geographic and institutional conditions.

4.4 Geographic Heterogeneity

Geographic differences were first examined by estimating the baseline fixed effects model for separate regional groups. Provinces located east of 105° longitude were classified as eastern, and those below 33° latitude were classified as southern. Membership in the Yangtze River Economic

Belt was identified using the indicator in the dataset. Statistical significance in one regional group and insignificance in another do not show that the estimated effects are different. The differences were tested using pooled models containing interaction terms between DFI and each regional indicator:

$$CESD_{icpt} = \beta_0 + \beta_1 DFI_{ct} + \beta_2 G_p + \beta_3 DFI_{ct} \times G_p + X'_{it}\gamma + \mu_p + \tau_t + \epsilon_{icpt} \quad (8)$$

In each pooled model, Gp is a binary regional indicator. It equals one for the region shown in the column heading and zero for its reference region. The three comparisons are East versus non East, South versus North, and the Yangtze River Economic Belt versus areas outside the belt. The coefficient β3 tests whether the association between DFI and the outcome differs between the two regions. For the reference region, the DFI coefficient is β1. For East, South, or the Yangtze River Economic Belt, the coefficient is the sum of β1 and β3.

Table 5A. Geographic Grouped Regressions

	East	Non-east	South	North	YREB	Non-YREB
DFI (standardized)	−0.186***	−0.930***	−0.259***	−0.229**	−0.213	−0.267***
	(0.070)	(0.276)	(0.096)	(0.091)	(0.134)	(0.077)
Age	0.041***	0.062***	0.044***	0.044***	0.044***	0.045***
	(0.003)	(0.008)	(0.003)	(0.004)	(0.004)	(0.003)
Rural	1.540***	2.005***	1.563***	1.740***	1.638***	1.651***
	(0.055)	(0.148)	(0.071)	(0.075)	(0.077)	(0.068)
Female	2.018***	2.639***	1.991***	2.213***	2.028***	2.147***
	(0.051)	(0.144)	(0.066)	(0.071)	(0.074)	(0.064)
Household size	−0.119***	−0.073	−0.093***	−0.151***	−0.082***	−0.141***
	(0.017)	(0.047)	(0.020)	(0.026)	(0.024)	(0.021)
Observations	52,842	7,592	31,536	28,898	25,593	34,841
R^2	0.074	0.087	0.077	0.084	0.082	0.075

Notes: The dependent variable is CESD. All models include year and province fixed effects and use heteroskedasticity-robust standard errors. YREB denotes the Yangtze River Economic Belt. * p < 0.10, ** p < 0.05, *** p < 0.01.

The estimated association between DFI and CESD was negative in all geographic groups. In eastern provinces, a one unit increase in DFI was associated with a 0.186 point decrease in CESD, with a standard error of 0.070. The estimated decrease was 0.930 points in non eastern provinces, with a standard error of 0.276. The corresponding decrease was 0.259 points in southern provinces and 0.229 points in northern provinces. Their standard errors were 0.096 and 0.091. Within the Yangtze River Economic Belt, a one unit increase in DFI was associated with a 0.213 point decrease in CESD. The standard error was 0.134, and the estimate was not statistically significant. Outside the belt, the estimated decrease was 0.267 points, with a standard error of 0.077, and the result was statistically significant. These separate estimates describe the pattern within each geographic group. Differences in their size or significance do not by themselves show that the association differs statistically across regions.

Table 5B. Pooled Geographic Interaction Tests

	East vs non-east	South vs north	YREB vs non-YREB
DFI main effect	−0.090	−0.305***	−0.277***
	(0.149)	(0.071)	(0.066)

DFI × East	−0.171		
	(0.127)		
DFI × South		0.073	
		(0.056)	
DFI × YREB			0.059
			(0.061)
Age	0.044***	0.044***	0.044***
	(0.003)	(0.003)	(0.003)
Rural	1.613***	1.650***	1.644***
	(0.052)	(0.051)	(0.051)
Female	2.096***	2.097***	2.097***
	(0.049)	(0.049)	(0.049)
Household size	−0.114***	−0.116***	−0.116***
	(0.016)	(0.016)	(0.016)
DFI slope: East / South / YREB	−0.261***	−0.232***	−0.219**
SE of DFI slope: East / South / YREB	(0.066)	(0.072)	(0.085)
Observations	60,434	60,434	60,434
R^2	0.079	0.079	0.079

Notes: The main DFI coefficient gives the estimated association for the reference region. The reference groups are non eastern provinces, northern provinces, and areas outside the Yangtze River Economic Belt. The interaction coefficient shows how much the DFI association in East, South, or the Yangtze River Economic Belt differs from that in its reference group. The DFI coefficients reported for these three regions are calculated by adding the main DFI coefficient, β1, to the interaction coefficient β3. All models include the regional indicator, the listed controls, year fixed effects, and province fixed effects. The reported standard errors allow for heteroskedasticity. * p < 0.10, ** p < 0.05, *** p < 0.01.

None of the interaction coefficients was statistically significant. The estimated DFI association in eastern provinces was 0.171 points more negative than that in non eastern provinces, with a standard error of 0.127. In southern provinces, the association was 0.073 points more positive than in northern provinces, with a standard error of 0.056. For the Yangtze River Economic Belt, the association was 0.059 points more positive than in areas outside the belt, with a standard error of 0.061.

The estimated DFI coefficients remained negative in all three regions. A one unit increase in DFI was associated with a 0.261 point decrease in CESD in eastern provinces and was significant at the 1 percent level. The estimated decrease was 0.232 points in southern provinces, with a p value of 0.001. In the Yangtze River Economic Belt, the decrease was 0.219 points, with a p value of 0.010. These estimates show negative associations within the three regions. The interaction tests do not show that their slopes differ from the corresponding reference groups.

Table 5C. Geographic Grouped Regressions for Self-Reported Health

	East	Non-east	South	North	YREB	Non-YREB
DFI (standardized)	−0.024**	−0.040	−0.034**	−0.026*	−0.052***	−0.022*
	(0.011)	(0.039)	(0.014)	(0.015)	(0.019)	(0.012)
Observations	55,070	7,850	32,870	30,050	26,650	36,270
R^2	0.057	0.043	0.062	0.052	0.065	0.050

Notes: The dependent variable is self-reported health. Higher self-reported-health values indicate

worse perceived health, so negative coefficients imply better self-rated health. All models include year and province fixed effects and use heteroskedasticity-robust standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 5D. Pooled Geographic Interaction Tests for Self-Reported Health

	East vs non-east	South vs north	YREB vs non-YREB
DFI main effect	0.002	−0.047***	−0.034***
	(0.021)	(0.011)	(0.010)
DFI × group	−0.034*	0.028***	0.012
	(0.018)	(0.009)	(0.009)
DFI slope: East / South / YREB	−0.031***	−0.018*	−0.023*
Observations	62,920	62,920	62,920
R^2	0.057	0.057	0.057

The geographic analysis for self reported health shows a clearer pattern than the CESD analysis. Higher values of self reported health indicate worse health, so a negative DFI coefficient represents an improvement in health. The DFI coefficient was negative in all six geographic groups and statistically significant in most groups. In the pooled models, the interaction for eastern provinces was negative and significant at the 10 percent level. The negative association between DFI and poor self reported health was stronger in eastern provinces than in non eastern provinces. The interaction for southern provinces was positive and statistically significant, showing a weaker association in southern provinces than in northern provinces. No significant difference was found between the Yangtze River Economic Belt and areas outside the belt.

The self reported health results show geographic differences between eastern and non eastern provinces and between southern and northern provinces. Similar differences were not consistently found in the CESD models. The geographic pattern may therefore depend on the health outcome being examined. These broad regional classifications may still overlook differences related to major urban growth centers. Table 6 assigns each observation to its nearest economic hub and reports both the coefficients estimated separately for each group and the interaction tests comparing the groups.

4.5 Nearest-Hub Heterogeneity

Each observation was assigned to the nearest of three economic hubs—Shanghai (SH), the Chengdu–Chongqing Economic Circle (CYEC), or the Greater Bay Area (GBA)—using squared geographic distance. Subgroup regressions describe within-hub associations, while a pooled model interacts DFI with hub indicators using SH as the reference category. The interaction coefficients, rather than comparisons of subgroup p-values, provide the formal tests of slope differences.

$$CESD_{icpt} = \beta_0 + \beta_1 DFI_{ct} + \delta_1 CYEC_c + \delta_2 GBA_c + \theta_1 (DFI_{ct} \times CYEC_c) + \theta_2 (DFI_{ct} \times GBA_c) + X'_{it}\gamma + \mu_p + \tau_t + \epsilon_{icpt} \quad (9)$$

Table 6A. Grouped Regressions by Nearest Economic Hub

	SH	CYEC	GBA
DFI (standardized)	−0.165*	−0.622***	−0.210
	(0.088)	(0.164)	(0.145)
Age	0.040***	0.054***	0.044***

	SH	CYEC	GBA
	(0.003)	(0.005)	(0.006)
Rural	1.278***	2.100***	1.427***
	(0.069)	(0.104)	(0.117)
Female	2.065***	2.445***	1.707***
	(0.064)	(0.096)	(0.112)
Household size	−0.159***	−0.072**	−0.061**
	(0.023)	(0.032)	(0.029)
Observations	33,871	16,084	10,479
R^2	0.075	0.103	0.063

Notes: The dependent variable is CESD. All models include year and province fixed effects and use heteroskedasticity-robust standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01.

The largest negative coefficient was found for CYEC. A one unit increase in DFI was associated with a 0.622 point decrease in CESD. The standard error was 0.164, and the estimate was significant at the 1 percent level. For SH, the estimated decrease was 0.165 points, with a standard error of 0.088. This estimate was significant only at the 10 percent level. The GBA coefficient indicated a decrease of 0.210 points, with a standard error of 0.145, but it was not statistically significant. These results describe the estimated association within each hub. Whether the coefficients differ across hubs needs to be examined using interaction tests.

Table 6B. Pooled Economic-Hub Interaction Test

Term	CESD
DFI: SH reference slope	−0.261***
	(0.071)
DFI × CYEC	0.148**
	(0.075)
DFI × GBA	0.013
	(0.066)
Age	0.045***
	(0.003)
Rural	1.560***
	(0.052)
Female	2.100***
	(0.048)
Household size	−0.111***
	(0.016)

Total DFI effect: SH	−0.261*** (0.071)
Total DFI effect: CYEC	−0.113 (0.098)
Total DFI effect: GBA	−0.248*** (0.077)
Observations	60,434
R^2	0.081

Notes: SH is the reference hub. Total effects are linear combinations from the pooled interaction model. The model includes hub indicators, age, rural residence, gender, household size, year fixed effects, province fixed effects, and heteroskedasticity-robust standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01.

In the pooled model, a one unit increase in DFI was associated with a 0.261 point decrease in CESD for SH. The standard error was 0.071, and the estimate was significant at the 1 percent level. The CYEC interaction coefficient was positive at 0.148, with a standard error of 0.075, and was significant at the 5 percent level. This result indicates that the DFI coefficient for CYEC was less negative than that for SH. After adding the interaction coefficient to the SH coefficient, the estimated CYEC slope was negative 0.113. Its standard error was 0.098 and its p value was 0.250. For GBA, the interaction coefficient was 0.013, with a standard error of 0.066, and was not statistically significant. The total GBA slope was negative 0.248, with a standard error of 0.077 and a p value of 0.001. The interaction test identified a difference between CYEC and SH, but no difference between GBA and SH.

The CYEC result differs between Tables 6A and 6B. In the separate regression, CYEC had the largest negative coefficient. Its total coefficient became smaller in the pooled model, and the interaction relative to SH was positive. The two models do not estimate the control variables and fixed effects in the same way. Separate regressions estimate these parameters independently for each hub, while the pooled model estimates them using the combined sample. The coefficient from a separate regression cannot directly test whether two hubs differ. The pooled interaction results provide evidence that the DFI slope differs between CYEC and SH. No statistically significant difference was found between GBA and SH.

Table 6C. Grouped Regressions by Nearest Economic Hub for Self-Reported Health

	SH	CYEC	GBA
DFI (standardized)	−0.025*	−0.072***	−0.017
	(0.014)	(0.023)	(0.022)
Observations	35,274	16,700	10,946
R^2	0.055	0.060	0.055

Notes: The dependent variable is self-reported health. Higher values indicate worse perceived health. All models include year and province fixed effects and use heteroskedasticity-robust standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 6D. Pooled Economic-Hub Interaction Test for Self-Reported Health

Term	SRH
DFI: SH reference slope	−0.037***
	(0.011)
DFI × CYEC	0.016
	(0.011)
DFI × GBA	0.013
	(0.010)
Total DFI effect: SH	−0.037*** (0.011)
Total DFI effect: CYEC	−0.020 (0.014)
Total DFI effect: GBA	−0.023** (0.012)
Observations	62,920
R^2	0.058

The results for self reported health were generally similar in direction to the CESD results, but the differences across hubs were less clear. DFI had a negative coefficient in all three hub groups. The estimates were statistically significant for SH and CYEC, but not for GBA. In the pooled model, neither the CYEC interaction nor the GBA interaction was significantly different from the SH reference. The total DFI coefficients remained negative for all three hubs, although the CYEC coefficient was not statistically significant. DFI was generally associated with lower self reported health scores, which indicate better health. The interaction tests did not find clear differences across hubs.

The hub classification identified a difference between CYEC and SH for CESD, but the same difference was not found for self reported health. This spatial pattern cannot explain what causes the variation. Digital infrastructure, access to financial services, population mobility, and the availability of health services may differ across hubs, but these mechanisms are not directly tested here. The next analysis considers one observable institutional factor, the local composition of hospitals. Separate group estimates and pooled interaction tests are both reported.

4.6 Hospital-Resource Heterogeneity

For each hospital tier k, we calculated its share by dividing the number of hospitals in that tier by the total number of tertiary, secondary, and primary hospitals. An indicator was set equal to one when the share was at least as large as the mean for the full sample, and zero otherwise. Separate regressions estimate the association between DFI and the outcome for provinces with lower and higher hospital shares. The difference between the two groups is tested using the following pooled interaction model:

$$\mathrm{CESD}_{icpt} = \beta_0 + \beta_1 \mathrm{DFI}_{ct} + \beta_2 \mathrm{High}_{k,pt} + \beta_3 \left(\mathrm{DFI}_{ct} \times \mathrm{High}_{k,pt}\right) + X'_{it}\gamma + \mu_p + \tau_t + \epsilon_{icpt} \quad (10)$$

Table 7A. Grouped Regressions by Hospital-Tier Share

	Low T3	High T3	Low T2	High T2	Low T1	High T1
DFI (standardized)	−0.381***	−0.280**	−0.266***	−0.397***	−0.202*	−0.272***
	(0.085)	(0.115)	(0.086)	(0.143)	(0.105)	(0.091)
Age	0.043***	0.047***	0.039***	0.049***	0.048***	0.041***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Rural	1.831***	1.331***	1.496***	1.788***	1.609***	1.669***

	(0.065)	(0.082)	(0.072)	(0.073)	(0.074)	(0.070)
Female	2.181***	1.970***	2.088***	2.107***	2.067***	2.125***
	(0.063)	(0.077)	(0.068)	(0.069)	(0.071)	(0.067)
Household size	−0.119***	−0.104***	−0.121***	−0.114***	−0.093***	−0.143***
	(0.021)	(0.024)	(0.024)	(0.021)	(0.021)	(0.024)
Observations	36,967	23,467	30,394	30,040	28,229	32,205
R^2	0.080	0.080	0.068	0.084	0.084	0.072

Notes: T3, T2, and T1 refer to the shares of tertiary, secondary, and primary hospitals, respectively. The dependent variable is CESD. All models include year fixed effects and province fixed effects. The reported standard errors allow for heteroskedasticity. * p < 0.10, ** p < 0.05, *** p < 0.01.

The DFI coefficient was negative in all six groups defined by hospital composition. In areas with a lower T3 share, a one unit increase in DFI was associated with a 0.381 point decrease in CESD, with a standard error of 0.085. In areas with a higher T3 share, the estimated decrease was 0.280 points, with a standard error of 0.115. For T2, the estimated decrease was 0.266 points in areas with a lower share and 0.397 points in areas with a higher share. The corresponding standard errors were 0.086 and 0.143. For T1, the estimated decrease was 0.202 points in areas with a lower share and 0.272 points in areas with a higher share. Their standard errors were 0.105 and 0.091. All six coefficients were statistically significant at conventional levels. The negative association between DFI and CESD was present across the different hospital compositions. These separate estimates do not show whether the coefficients differ statistically between areas with lower and higher hospital shares. This question is examined using the pooled interaction models.

Table 7B. Pooled Hospital-Tier Interaction Tests

	Tertiary share	Secondary share	Primary share
DFI slope: low-share group	−0.396***	−0.279***	−0.159**
	(0.074)	*(0.067)*	*(0.078)*
DFI × High share	0.215***	0.105	−0.159***
	(0.056)	*(0.070)*	*(0.060)*
Age	0.045***	0.044***	0.045***
	(0.003)	*(0.003)*	*(0.003)*
Rural	1.641***	1.643***	1.643***
	(0.051)	*(0.051)*	*(0.051)*
Female	2.097***	2.097***	2.097***
	(0.049)	*(0.049)*	*(0.049)*
Household size	−0.115***	−0.115***	−0.115***
	(0.016)	*(0.016)*	*(0.016)*
Total DFI effect: high share	−0.181**	−0.173*	−0.318***
High-share total-effect SE	*(0.070)*	*(0.095)*	*(0.069)*
Observations	60,434	60,434	60,434
R^2	0.079	0.079	0.079

Notes: The interaction coefficient measures the difference between areas with higher and lower hospital shares. The total DFI coefficient for areas with a higher share is calculated by adding the interaction coefficient to the coefficient for areas with a lower share. All models include the

hospital share indicator, the listed controls, year fixed effects, and province fixed effects. The reported standard errors allow for heteroskedasticity. * p < 0.10, ** p < 0.05, *** p < 0.01.

For tertiary hospitals, the interaction coefficient was positive at 0.215. Its standard error was 0.056, and it was significant at the 1 percent level. The negative association between DFI and CESD was smaller in areas with a higher T3 share. The total DFI coefficient for these areas was negative 0.181, with a standard error of 0.070 and a p value of 0.010.

The interaction coefficient for the T2 share was 0.105, with a standard error of 0.070, and was not statistically significant. The DFI coefficients for areas with higher and lower T2 shares could not be distinguished statistically. In areas with a higher T2 share, the total DFI coefficient was negative 0.173. The standard error was 0.095, and the p value was 0.068.

A different pattern was found for primary hospitals. The interaction coefficient was negative 0.159, with a standard error of 0.060, and was significant at the 1 percent level. The negative association was stronger in areas with a higher T1 share. The total DFI coefficient in these areas was negative 0.318, with a standard error of 0.069, and was significant at the 1 percent level. The interaction tests support differences between areas with higher and lower shares of tertiary and primary hospitals. No clear difference was found for the secondary hospital share.

The interaction coefficients for tertiary and primary hospitals had opposite signs. A higher tertiary hospital share was associated with a smaller negative DFI coefficient, while a higher primary hospital share was associated with a larger negative coefficient. Digital financial services may be more useful when they are combined with primary care that is easily available to local residents. Their additional contribution may be smaller in areas where the hospital system is more concentrated in tertiary institutions. This explanation is not directly tested by the models. Hospital composition may also reflect differences in urbanization, local fiscal capacity, or other conditions that are not fully captured by the included controls.

Table 7C. Grouped Regressions by Hospital-Tier Share for Self-Reported Health

	Low T3	High T3	Low T2	High T2	Low T1	High T1
DFI (standardized)	−0.048***	−0.011	−0.035**	−0.019	−0.014	−0.041***
	(0.013)	(0.018)	(0.014)	(0.021)	(0.015)	(0.014)
Observations	38,472	24,448	31,325	31,595	29,659	33,261
R^2	0.060	0.054	0.052	0.053	0.057	0.053

Notes: The dependent variable is self-reported health. T3, T2, and T1 denote tertiary-, secondary-, and primary-hospital shares, respectively. All models include year and province fixed effects and use heteroskedasticity-robust standard errors. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 7D. Pooled Hospital-Tier Interaction Tests for Self-Reported Health

	Tertiary share	Secondary share	Primary share
DFI slope: low-share group	−0.047***	−0.036***	−0.009
	(0.011)	(0.011)	(0.012)
DFI × High share	0.023***	0.037***	−0.034***
	(0.009)	(0.011)	(0.009)
Total DFI effect: high share	−0.024**	0.001	−0.043***
High-share total-effect SE	(0.011)	(0.014)	(0.011)
Observations	62,920	62,920	62,920
R^2	0.057	0.057	0.057

The self reported health results also varied with hospital composition. In the separate regressions,

DFI was significantly associated with lower self reported health scores in areas with lower T3 shares, lower T2 shares, and higher T1 shares. The coefficients in the other three groups were negative but not statistically significant. The pooled models provide clearer evidence of differences between the groups. For T3, the interaction coefficient was positive at 0.023 and significant at the 1 percent level. The total DFI coefficient in areas with a higher T3 share remained negative at 0.024 and was statistically significant. For T2, the positive interaction coefficient of 0.037 offset the negative coefficient found in areas with a lower share. The total coefficient in areas with a higher T2 share was 0.001, indicating almost no association between DFI and self reported health.

The T1 interaction coefficient was negative at 0.034 and significant at the 1 percent level. The total DFI coefficient in areas with a higher T1 share was negative 0.043 and remained statistically significant. A higher primary hospital share was associated with a stronger negative DFI coefficient in both the CESD and self reported health models. The results for secondary hospitals were less consistent across the two outcomes. The interaction was not significant for CESD but was significant for self reported health. Hospital composition may also reflect differences in population characteristics and other local conditions. Table 8 examines whether the main estimates remain after matching observations on the observed covariates and using the recentered instrument.

4.7 Robustness Checks

As a robustness check, we reweighted the sample using propensity score matching. Observations from the 2015 and 2018 survey waves were coded as one, while observations from 2011 and 2013 were coded as zero. A logit model estimated the probability of belonging to the later survey period using household size, age, household size squared, and age squared. Each observation was matched to the observation with the closest propensity score in the other period. Ties were retained, and observations outside the area of common support were excluded. The matching weights were then applied when estimating the fixed effects outcome models [45].

Columns 1 and 2 of Table 8 report the HDFE coefficients for standardized DFI using these matching weights. These coefficients describe the association in the reweighted sample. Columns 3 and 4 use the recentered instrument proposed by Borusyak and Hull and described in Section 4.3 [49]. The matching weights are not applied in these two models. Columns 5 and 6 use the original sample and the baseline HDFE specification. Their standard errors are clustered by respondent ID, allowing observations from the same respondent to have correlated errors across survey waves.

$$\log\left[\frac{P(\text{Post2015}_{it}=1|W_{it})}{1-P(\text{Post2015}_{it}=1|W_{it})}\right] = \alpha_0 + \alpha_1\text{HHSIZE}_{it} + \alpha_2\text{AGE}_{it} + \alpha_3\text{HHSIZE}_{it}^2 + \alpha_4\text{AGE}_{it}^2 \quad (11)$$

Table 8. Robustness Estimates from Propensity-Score-Weighted HDFE, Recentered-Instrument 2SLS, and Individual-Clustered HDFE Models

	PS-weighted HDFE: CESD	PS-weighted HDFE: SRH	Recentered IV: CESD	Recentered IV: SRH	Cluster-ID HDFE: CESD	Cluster-ID HDFE: SRH
DFI (standardized)	−0.339***	−0.036***	−0.228**	−0.032**	−0.271***	−0.033***
	(0.077)	*(0.012)*	*(0.102)*	*(0.015)*	*(0.070)*	*(0.011)*
Observations	60,264	60,206	60,434	62,920	60,434	62,920
R^2	0.082	0.057	0.050	0.032	0.079	0.057

Notes: Columns 1 and 2 use matching weights to estimate the relationship between standardized

DFI and the two health outcomes. The matching is based on whether an observation comes from the 2015 and 2018 waves or from the 2011 and 2013 waves. Household size, age, and their squared values are used to calculate the matching scores. Ties are retained, and observations without a comparable match are excluded. Six untreated observations were excluded from the CESD sample. The estimates in these columns are weighted regression coefficients, not estimates of the average treatment effect on the treated. Columns 3 and 4 report results using the recentered instrument without matching weights. Columns 5 and 6 report the baseline HDFE results without weights and cluster the standard errors by respondent. All models include the listed controls, year fixed effects, and province fixed effects.* p < 0.10, ** p < 0.05, *** p < 0.01.

The negative relationship between DFI and both health outcomes remained after matching. A one standard deviation increase in DFI was related to a 0.339 point decrease in CESD. The standard error was 0.077, and the estimate was significant at the 1 percent level. The sample included 60,264 observations. For self reported health, the estimated decrease was 0.036 points. The standard error was 0.012, and the p value was 0.003, based on 60,206 observations.

The results from the recentered instrument were similar. A one unit increase in predicted DFI was related to a 0.228 point decrease in CESD and a 0.032 point decrease in self reported health. Both estimates were statistically significant and close to the baseline HDFE results. The estimates also remained significant when the standard errors were clustered by respondent. In this model, a one standard deviation increase in DFI was related to a 0.271 point decrease in CESD and a 0.033 point decrease in self reported health.

The matching procedure removed only six observations from the CESD comparison, and both matched samples still contained more than 60,000 observations. The weighted results were therefore not produced by removing a large part of the sample. They were somewhat larger than the original estimates in Table 2. Overall, the negative coefficients appeared in the baseline analysis and remained in the alternative models. The results are fairly stable, although the robustness checks cannot address every possible source of bias.

4.8 Statistical Mediation

We considered two possible mediators that were selected before the analysis: the number of primary hospitals and telecommunications business volume per person. For each mediator M, three equations were estimated using the same control variables, year fixed effects, and province fixed effects:

$$CESD_{icpt} = cDFI_{ct} + X'_{it}\gamma + \mu_p + \tau_t + \epsilon_{icpt}, \quad (12)$$

$$M_{icpt} = aDFI_{ct} + X'_{it}\delta + \mu_p + \tau_t + \nu_{icpt}, \quad (13)$$

$$CESD_{icpt} = c'DFI_{ct} + bM_{pt} + X'_{it}\theta + \mu_p + \tau_t + \xi_{icpt}. \quad (14)$$

The indirect association is calculated by multiplying coefficient a by coefficient b. Standard errors for the two individual coefficients are calculated using the HC1 method. The distribution of their product may not follow a normal distribution, so the confidence interval and p value are based on 1,000 bootstrap samples [46]. The Benjamini–Hochberg method is used to adjust for multiple testing across the four indirect associations examined in the full analysis [47]. The table reports the two mediators discussed in this section.

Table 9. Three-Step, Bootstrap, and FDR Results for Selected Mediators

Mediator	N	Total c	Path a	Path b	Direct c′	Indirect a×b	Bootstrap 95% CI	Boot. p	FDR p	Reduction %
Primary	60,434	−0.2712***	14.2274***	−0.001037***	−0.2565***	−0.01475	[−0.02320,	0.000	0.000	5.44

Mediator	N	Total c	Path a	Path b	Direct c′	Indirect a×b	Bootstrap 95% CI	Boot. p	FDR p	Reduction %
hospitals							−0.00621]			
Telecom business per capita	59,238	−0.2879***	0.03610***	−4.2343**	−0.1351	−0.15287	[−0.27766, −0.01351]	0.024	0.026	53.09

Notes: All three equations control for age, rural residence, gender, and household size and include year fixed effects and province fixed effects. Standard errors for the individual paths are calculated using the HC1 method. Confidence intervals for the indirect associations are based on 1,000 bootstrap samples. The false discovery rate adjustment covers four indirect associations selected before the analysis, although only the two mediators discussed in this section are shown in the table. The reduction percentage compares the absolute size of the total and direct DFI coefficients using the same observations with complete data. ** p < 0.05, *** p < 0.01 for individual regression paths.

DFI was positively related to the number of primary hospitals. A one unit increase in DFI was associated with 14.2274 additional primary hospitals, and this relationship was significant at the 1 percent level. After DFI was controlled, one additional primary hospital was associated with a 0.001037 point decrease in CESD. This estimate was also significant at the 1 percent level. Multiplying these two coefficients gave an indirect association of negative 0.01475. The bootstrap confidence interval ranged from negative 0.02320 to negative 0.00621, and the adjusted p value was below 0.001. The direct DFI coefficient remained negative at 0.2565 and significant at the 1 percent level. Its absolute size decreased by 5.44 percent.

Telecommunications business volume showed a larger indirect association. A one unit increase in DFI was related to a 0.03610 unit increase in telecommunications volume per person. One unit of telecommunications volume was then associated with a 4.2343 point decrease in CESD after DFI was controlled. The estimated indirect association was negative 0.15287, with a bootstrap confidence interval from negative 0.27766 to negative 0.01351. The bootstrap p value was 0.024, and the adjusted p value was 0.026. In the sample of 59,238 observations with complete data, the direct DFI coefficient decreased to negative 0.1351 and was no longer statistically significant. Its absolute size was 53.09 percent smaller than the total coefficient. And both indirect associations remained significant after bootstrap estimation and adjustment for the four tests.

5. Discussion

5.1 Principal Findings

This study examined the relationship between digital financial inclusion, or DFI, and the psychological health of middle aged and older adults in China. In the main HDFE models, higher DFI was related to fewer depressive symptoms and better self reported health. A one standard deviation increase in DFI was associated with a 0.271 point decrease in CESD and a 0.033 point decrease in the self reported health score. Lower scores indicate better health for both outcomes. CESD mainly measures depressive symptoms, while self reported health gives a more general assessment of a person’s physical and psychological condition. Similar results from the two measures provide some support that the finding is not limited to one definition of health. The ordered response models also produced negative estimates. The main pattern is modest but appears across different outcome measures.

The instrument results require a more careful interpretation. The instruments based on the pilot program and unadjusted broadband data produced much larger coefficients than the HDFE models. These estimates may apply to populations whose DFI exposure responds more strongly to

broadband development. Their large size also makes them difficult to compare directly with the baseline results. We then used the recentering method proposed by Borusyak and Hull [49]. This method removes the component of leave-one-out DFI growth that is common to provinces in the same year and uses the remaining relative variation. The instrument strongly predicted DFI. A one unit increase in predicted DFI was associated with a 0.228 point decrease in CESD and a 0.032 point decrease in self reported health. These estimates were close to the HDFE coefficients. The similarity is useful, but it does not prove that the instrument affects health only through DFI. It shows that the result remains when identification is based on provincial deviations from the common DFI trend.

5.2 Digital Inclusion and Psychosocial Health

Previous studies have connected internet access and digital finance with the health of older adults in China. Internet use may support mental health by increasing social participation, improving access to information, and helping older adults maintain contact with family and community members [7,8]. Studies focusing on DFI have also reported improvements in health and mental health, although the estimated size differs across populations, outcomes, and research designs [6,16,17].

The present study contributes to this literature in three ways. It examines depressive symptoms and general self reported health separately, rather than relying on a single health measure. It also treats DFI as part of the local financial and information environment, not only as an individual decision to use the internet. Older adults may benefit from this environment without personally using complex online financial services. Easier household transfers, better access to local services, and assistance from younger family members are possible examples. The study also uses broadband related instruments and applies the recentering method proposed by Borusyak and Hull [49]. This adjustment removes the component of DFI growth shared by provinces in the same year. The resulting estimates are close to the baseline HDFE results, providing additional evidence that the main finding is not limited to one estimation method.

Several explanations are possible. Digital payments and credit services can reduce the time and cost required to buy goods, pay bills, receive transfers, or deal with temporary financial difficulty. Better access to information may help people understand medical services and social benefits. These possibilities are related to Grossman's view that health is produced through resources, information, and the use of time [24].

Digitalization may also create difficulties. Older people with limited digital skills can face unfamiliar interfaces, fraud, privacy risks, and dependence on family members. The average negative coefficient does not mean that every digital financial service benefits every older adult. It reflects the average relationship observed during an uneven expansion of digital finance and broadband infrastructure in China.

5.3 Geographic and Institutional Heterogeneity

The geographic results were not the same for the two health outcomes. In the CESD models, the interaction tests did not find clear differences between East and non East, South and North, or provinces inside and outside the Yangtze River Economic Belt. For self reported health, differences were found between East and non East and between South and North. There was no significant difference for the Yangtze River Economic Belt comparison.

The hub classifications gave another pattern. GBA did not have a consistently different DFI coefficient. For CESD, the coefficient for CYEC differed significantly from the SH reference. The

same difference was not found for self reported health. Major economic hubs may spread digital services and information differently across nearby areas, but the estimates do not directly test these movements. Research on growth poles suggests that infrastructure, service concentration, and connections between regions affect how benefits move beyond a central city [38]. The results here indicate that specific institutional settings may be more informative than broad regional categories.

Hospital composition was also related to the estimates. For CESD, the negative DFI coefficient was smaller in provinces with a higher share of tertiary hospitals and larger in provinces with a higher share of primary hospitals. No significant difference was found for the share of secondary hospitals. The self reported health models also produced significant differences for tertiary and primary hospital shares. A difference for the secondary hospital share appeared only in the self reported health model.

One possible explanation concerns the different functions of hospitals. In places with many tertiary hospitals, residents may already have better access to specialized diagnosis and treatment. Digital finance may add less to the removal of health related constraints in these areas. Primary hospitals usually provide routine monitoring, referrals, and local care. Digital payment and information services may be more useful when primary care is easy to reach. This interpretation agrees with evidence that the location and concentration of health care resources influence access among older adults [36,37].

5.4 Potential Pathways

The analysis considered two possible pathways: the number of primary hospitals and telecommunications business volume per person. The indirect association through primary hospitals was negative 0.01475. After primary hospital supply was included, the absolute DFI coefficient decreased by 5.44 percent and remained statistically significant. This is a small change, suggesting that primary hospital availability may account for only a limited part of the observed relationship.

Telecommunications volume produced a larger result. Its indirect association was negative 0.15287, and the absolute DFI coefficient decreased by 53.09 percent. The direct DFI coefficient was no longer statistically significant in this model. Both indirect associations remained significant after bootstrap testing and adjustment for the four comparisons [47]. The two percentages come from different samples, so they should not be compared as if they were calculated from the same total coefficient.

These results are statistical decompositions, not confirmed causal pathways. DFI, telecommunications activity, hospital supply, and mental health may all change with local economic development, administrative capacity, or household demand. The data also do not clearly establish whether changes in the mediators happened before changes in health. The telecommunications result should not be interpreted as showing that exactly 53.09 percent of a causal DFI effect operates through telecommunications. It identifies a possible pathway that deserves more direct study. Future research could measure digital skills, actual service use, social contact, and exposure to online risks.

5.5 Robustness and Methodological Interpretation

The robustness checks address different parts of the analysis. Propensity score matching reweights observations using measured characteristics under the assumption that the relevant selection is captured by those variables [45]. The weighted models continued to show negative DFI

coefficients for CESD and self reported health. Only six untreated observations were outside the area of common support in the CESD sample.

Clustering by respondent allows observations from the same person to have correlated errors across survey waves. Both baseline coefficients remained statistically significant with this adjustment. The recentered instrument addresses another issue. Common national DFI growth may enter a formula instrument even when it does not provide useful differences across provinces. Recentring removes this common component before combining the remaining growth variation with initial broadband exposure [49]. The Kleibergen–Paap statistics show that the adjusted instrument strongly predicts DFI [43].

The negative sign appeared in the CESD models, the self reported health models, the ordered response models, the weighted models, and the models using the recentered instrument. This consistency reduces concern that the result comes only from one model or one method of calculating standard errors. Some uncertainty remains. The HDFE models include province and year fixed effects, not individual fixed effects. The instrument models use the variation generated by the instrument and may estimate an effect for a particular part of the population. The evidence is more safely described as a stable negative relationship between DFI and poor psychological health across several specifications.

5.6 Strengths and Limitations

The study combines four waves of a large national survey on ageing with local information on digital finance, broadband access, hospital resources, and economic conditions. It examines both depressive symptoms and general self reported health. The ordered response analysis checks whether the result depends on treating an ordered outcome as continuous. The geographic and hospital analyses also allow the DFI coefficient to vary across local settings.

Different methods are used for different concerns. The fixed effects models control for stable provincial differences and common changes over time. Matching changes the weight given to observations with similar measured characteristics. Clustering accounts for repeated observations from the same respondent. The recentered instrument uses provincial differences relative to common DFI growth. Stating these methods separately makes their assumptions easier to see.

Several limitations remain. The study is observational, and the assumption that the instrument affects health only through DFI cannot be tested directly. Missing information also produces different samples across outcomes and covariates. The estimates may be selective if missingness is related to health or digital participation in ways that are not observed.

Missing values for broadband use were coded as zero under the data construction rule. This keeps more observations in the sample, but a missing response may not always mean that broadband use was zero. CESD and self reported health are both reported by respondents. Self reported health is a general ordered assessment and is not a clinical diagnosis.

The measures of hospital supply and telecommunications activity are defined at the provincial level. They do not show service quality, affordability, individual use, or digital ability. The study covers Chinese adults aged 45 years and older between 2011 and 2018. Digital platforms, regulation, and user habits have changed since then. The results may not fully describe the current digital environment and should not be directly extended to other countries.

6. Policy Implications

Digital inclusion may be relevant to ageing policy as well as financial development. Expanding broadband and digital payment services can improve access, but infrastructure alone may not be

enough. Older users may also need simple interfaces, protection from fraud, privacy support, and practical help in the community. Policy evaluation should consider depressive symptoms and general health, not only the number of accounts or digital transactions.

Primary care may be a useful place for connecting digital and health services. Local governments and service providers could link digital payment and information systems with primary care appointments, follow up for chronic disease, reimbursement, and referrals. Offline services should remain available for people who cannot or do not want to use online systems. The larger negative DFI coefficient in areas with a higher primary hospital share does not mean that adding more hospitals will automatically improve mental health. It suggests that digital services may work better when local institutions can turn them into practical support.

The geographic results do not support one policy design for every region. Local service networks, population characteristics, and links between central cities and surrounding areas differ considerably. Monitoring should separate access from actual use and examine whether older adults, rural residents, and people with poor initial health receive the intended benefits.

Telecommunications activity was related to a relatively large part of the DFI coefficient, but it has not been established as a causal pathway. Pilot programs could collect information on digital use, social contact, primary care access, and mental health over time. Such evidence would give a better basis for deciding which services should be expanded.

7. Conclusion

Using four waves of CHARLS linked with local digital finance and institutional data, this study finds that higher DFI is related to fewer depressive symptoms and better self reported health among middle aged and older adults in China. The negative association remains across different outcomes and several robustness checks. Estimates from the recentered broadband instrument are also close to the main HDFE results.

The coefficient varies more across some hospital settings and economic hubs than across broad geographic regions. A higher primary hospital share is generally related to a stronger negative DFI coefficient, while a higher tertiary hospital share is related to a smaller one. The statistical decomposition identifies a small component related to primary hospitals and a larger component related to telecommunications activity. Neither result establishes a causal pathway.

The findings suggest that the health relevance of DFI depends partly on the local services through which older adults obtain information, communicate, and receive care. Digital infrastructure may be more useful when it is combined with accessible primary care and practical protection for older users.

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