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The impact of internet use on the well-being of rural residents: evidence from formerly impoverished areas in China

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The rise of the digital economy and advances in ICTs, especially the internet, have profoundly reshaped rural residents' work and daily life. Based on original survey data from 1,037 households in China's formerly impoverished regions, this study extends Sen's Capability Approach into the digital domain and proposes a "psychology–health–economy" analytical framework. Employing multiple econometric techniques, we systematically examine the effects of internet use on the multidimensional well-being of rural residents. The findings indicate that internet use significantly enhances well-being by positively influencing happiness, self-reported health status, and household income. Mechanism analyses reveal that these effects are primarily mediated through enhanced self-efficacy, improved access to health-related information, and increased opportunities for non-agricultural employment. Furthermore, the benefits of internet use are more pronounced among younger and middle-aged individuals, underscoring the heterogeneous impacts of digital technology across different age groups. Based on these insights, we propose a hybrid "infrastructure–capability–service" intervention strategy to enhance digital inclusion. This approach calls for strengthening rural internet infrastructure, fostering digital literacy, and developing accessible online service platforms, with the overarching goal of enhancing the multidimensional well-being of rural populations and supporting sustainable rural revitalization.

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Introduction

The internet facilitates access to a wide range of resources and services, enabling users to obtain information efficiently and maintain social connections (Nakagomi et al., 2022). During the COVID-19 pandemic in particular, the internet provided users with health-promoting information and sustained social interactions, thereby establishing itself as a key social determinant of well-being (Staniewski and Awruk, 2022). However, the relationship between internet use and well-being may be bidirectional, as unequal social and economic conditions influence individuals' experiences of digital exclusion, which in turn reinforces barriers to internet access and use (Holmes and Burgess, 2022). Despite these challenges, growing evidence suggests that the advancement of digital technologies can contribute to poverty alleviation (Dzator et al., 2023). The internet is increasingly recognized as a critical driver for narrowing information gaps and promoting inclusive development. Nonetheless, the digital divide persists, as evidenced by disparities in internet access and digital engagement across demographic groups—for instance, between the wealthy and the poor, and between older and younger populations. Internet use may help older adults maintain intergenerational ties, thereby improving their subjective well-being (Li and Zhou, 2021), yet its impact on the well-being of adolescents appears to be limited (Schemer et al., 2021). Moreover, the deprivation of digital rights can result in adverse health outcomes, economic marginalization, and systemic inequalities (Early and Hernandez, 2021), underscoring the role of internet access as a key transmission mechanism for enhancing individual well-being in the digital age (Li et al., 2025).

In China, the deep integration of internet technologies into rural areas has become a vital pillar supporting national strategies for poverty alleviation and rural revitalization. Following the elimination of absolute poverty in 2020, the role of digital technologies in rural development has grown increasingly significant. Improving digital literacy has been shown to reduce relative poverty and promote common prosperity among rural households (Zhang et al., 2024). It also helps mitigate the risk of falling back into poverty by facilitating access to local non-agricultural employment and by improving income-generating opportunities, such as supporting migrant labor mobility, enhancing entrepreneurial outcomes, and expanding the scale of rural entrepreneurship. (Bahia et al., 2024; Zhou et al., 2024). As policy attention shifts toward consolidating the achievements of poverty alleviation and enhancing multidimensional well-being, it remains critical to examine the broader impacts of internet use on the lives of rural residents. Internet access can improve farmers' well-being in both objective and subjective dimensions (Meng et al., 2024), contributing to the multidimensional poverty alleviation, improving access to public services, and enhancing subjective well-being (Yang et al., 2021). Against the backdrop of internet technologies profoundly transforming rural development, a key challenge is how to effectively leverage the internet to empower households in formerly impoverished regions, consolidate poverty alleviation gains, narrow the urban-rural development gap, and foster sustainable rural development.

Sen's Capability Approach offers a foundational framework for analyzing the mechanisms through which well-being is generated in the digital era. At its core, well-being is defined by the substantive freedoms individuals possess to pursue the kind of life they value (Miletzki and Broten, 2017). This perspective emphasizes the synergistic expansion of health promotion, psychological empowerment, and economic opportunity, rather than a narrow focus on income growth. A growing body of research has examined the internet's influence across various dimensions of well-being, including economic, health-related, psychological, and subjective aspects, highlighting its role in facilitating income diversification (Li et al., 2021; Nguyen et al., 2022). Internet literacy and users' risk perceptions jointly contribute to healthier behaviors, such as reduced engagement in risky activities and increased utilization of preventive health services (Ahadzadeh et al., 2015; Hunsaker et al., 2021; Chen and Liu, 2022; Van Deursen, 2022). From a psychological perspective, internet use has a dual effect: it can enhance social support networks, but it may also lead to internet addiction, resulting in emotional changes and impaired self-control (Omar et al., 2020; Li and Zhou, 2021).

China achieved a comprehensive victory over income-based poverty in 2020, with all officially designated poverty-stricken regions removed from the national poverty list. However, compared with the developed areas, these formerly impoverished regions continue to face significant challenges, including underdeveloped economies, inadequate infrastructure, and a heightened risk of falling back into poverty. Therefore, enhancing well-being in these regions remains a critical priority. This study extends Sen's Capability Approach into the digital domain by constructing a comprehensive "psychology–health–economy" analytical framework, thereby advancing the theoretical boundaries of existing research. The framework reorients the focus of digital inclusion studies from a narrow emphasis on economic outcomes to a broader consideration of psychosocial and health dimensions, in alignment with the core principles of overall well-being outlined in the United Nations Sustainable Development Goals (SDGs). Although prior research has extensively validated the mediating role of social capital in the relationship between internet use and well-being (Pang, 2018; Sun et al., 2023), the mechanisms involving psychological efficacy, informational access, and economic opportunity transformation remain underexplored. This study identifies three key pathways through which the internet enhances the well-being of rural residents: increase self-efficacy, improve access to health-related information, and expand opportunities for non-agricultural employment. These findings offer empirical enrichment to the literature on digital empowerment mechanisms. By focusing on formerly impoverished areas, this research also highlights the heterogeneous impacts of internet use in contexts marked by entrenched poverty, providing a theoretical foundation for refining digital poverty alleviation policies and offering practical insights toward the realization of "common prosperity".

Based on survey data from 1,037 rural households in formerly impoverished areas, this study employs a range of econometric techniques—including ordered probit (Oprobit) regression, ordinary least squares (OLS), instrumental variable probit (IV-Probit), two-stage least squares (2SLS), and the Karlson–Holm–Breen (KHB) method—to identify the causal effects of internet use on happiness, self-rated health, and household income. In addition, we examine the mediating roles of self-efficacy, access to health-related information, and participation in non-farm employment, as well as explore the heterogeneity across different age groups. The remainder of this paper is organized as follows: Section 2 outlines the theoretical framework; Section 3 describes the data and methodology; Section 4 presents the empirical results, including robustness checks and mechanism analysis; Section 5 discusses heterogeneity and policy implications; and Section 6 concludes the paper.

Theoretical Framework

The internet significantly enhances rural residents' subjective well-being through its diverse functionalities. First, online learning, online social interaction, and online entertainment are important ways to improve the subjective well-being of rural residents (Zhou et al., 2023). Similarly, social self-efficacy can enhance individuals' perceived online social support and contribute to higher levels of life satisfaction consequentially (Liu and LaRose, 2008). Second, the role of online consumption is also noteworthy. Research indicates that rural e-commerce services can also significantly improve farmers' subjective well-being (Jin et al., 2020). Moreover, online shopping enhances consumers' long-term subjective well-being by increasing the proportion of hedonic consumption, and this effect is more pronounced among rural consumers than their urban counterparts (Wang and Jia, 2023).

Internet self-efficacy plays a critical role in shaping users' well-being. Fulfilling psychological needs through online communication can enhance individuals' social self-efficacy, thereby promoting greater subjective well-being (Li et al., 2014). Research has shown that altruistic online behavior can indirectly enhance well-being by strengthening individuals' sense of self-efficacy (Zheng et al., 2016). Higher levels of social media self-efficacy significantly improve subjective well-being by boosting self-esteem and reducing feelings of loneliness (Chen and Gao, 2023). Moreover, internet use experience, positive outcome expectations, successful performance accomplishments, and proactive personality traits can also positively influence self-efficacy judgments (Eastin and LaRose, 2000; Lin et al., 2013), thereby creating a reinforcing cycle of confidence and sustained engagement. Nevertheless, the potential negative consequences of internet use should not be overlooked. For instance, internet addiction, such as compulsive gaming or excessive short video consumption, can lead to a decline in subjective well-being (Omar et al., 2020).

The internet, as a vital supplementary health resource (Suziedelyte, 2012), influences the health outcomes of rural residents through two primary pathways: information acquisition and behavioral intervention. However, its effectiveness is significantly shaped by both individual capabilities and broader structural constraints. First, access to health-related information serves as a key mediating mechanism. Research has shown that individuals with higher levels of e-health literacy are more likely to actively seek health information, ultimately leading to the adoption of healthier behaviors (Kivits, 2009; Sheng and Simpson, 2013). Further evidence suggests that individuals who seek health information online tend to hold stronger health beliefs, as internet use enhances awareness of health risks and promotes proactive health management (Dutta-Bergman, 2004).

However, the digital divide between urban and rural areas, coupled with concerns over the credibility of online information, significantly constrains the health benefits derived from internet use. Empirical studies have shown that, due to lower levels of education and limited broadband infrastructure, rural residents are less likely to search for health information online compared to their urban counterparts (Hale et al., 2010). At the same time, the potential negative consequences of online health engagement must be acknowledged. While the internet facilitates rapid access to health-related knowledge, the proliferation of unverified and pseudoscientific content can mislead users and lead to inappropriate health decisions (Cheng et al., 2022). It is also critical to consider group-level heterogeneity. For example, research has found that individuals with higher educational attainment are significantly more likely to engage in online consultations with medical professionals (Hong and Cho, 2017; Bilgin et al., 2019). Similarly, low-income populations have been shown to be significantly less likely to utilize the internet as a source of health information (Dart, 2008; AlGhamdi and Moussa, 2012; Yoon et al., 2020).

The internet significantly enhances rural residents' income by transforming the rural economic landscape, primarily through the expansion of non-agricultural employment opportunities and the restructuring of income sources. First, rural e-commerce and online entrepreneurship have emerged as direct drivers of income growth. For instance, one study found that rural e-commerce exerts a significantly positive impact on household income (Chao et al., 2021). Another study further demonstrated that farmers engaged in e-commerce activities earn markedly more than those who are not, with income gains primarily attributed to increased sales revenue (Li et al., 2021). Moreover, the influence of internet use on entrepreneurial intent and income levels among rural residents has been found to surpass that observed among their urban counterparts (Wang et al., 2022).

Second, non-agricultural employment plays a pivotal role in income enhancement. Existing research indicates that internet use helps reduce income inequality among rural households, with the level of non-agricultural employment serving as a key mediating factor between internet usage and income disparity (Zhang et al., 2023). Another study highlighted that the expansion of non-agricultural employment opportunities enables a shift in rural income structures—from dependency on natural resources to more diversified sources—thereby promoting sustained income growth (Zhou et al., 2020). Therefore, this study formulates the following research hypotheses:

H1: Internet use has a significant positive effect on the multidimensional well-being of rural residents, including happiness, health, and income.

H2: Internet self-efficacy mediates the relationship between internet use and the subjective well-being of rural residents.

H3: Access to health-related information serves as a mediating mechanism through which internet use influences the health status of rural residents.

H4: Non-agricultural employment opportunities mediate the relationship between internet use and the economic income of rural residents.

Data and Methods

Study area and data collection. The data for this study were obtained from a household survey conducted by the research team in July 2022 in China. Specifically, we selected the Wuling Mountain, Dabie Mountain, and Qinba Mountain areas in Hubei Province, based on the 14 contiguous poverty-stricken areas identified in the Outline of Rural Poverty Alleviation and Development (2011–2020). Compared to the broader rural regions of China, these contiguous poverty-stricken areas exhibit three distinct characteristics:

(1) Geographic Environment: These areas are characterized by complex terrain, frequent natural disasters, and severe ecological degradation—such as rocky desertification and soil erosion—which constrain agricultural productivity.
(2) Economic Structure: The local economy remains largely reliant on traditional agriculture, with minimal industrial diversification and limited opportunities for non-agricultural employment.
(3) Public Services and Infrastructure: Due to the geographic isolation, transportation, education, and healthcare services are underdeveloped in these areas. In particular, digital infrastructure lags behind the national rural average, resulting in lower internet penetration rates.

A stratified sampling method was used to ensure representativeness. First, five counties were selected from the three target regions: Jianshi County, Xianfeng County, Yunxi County, Yunyang District (formerly Yun County), and Xiaochang County. Next, three towns were randomly selected within each county, followed by the random selection of three administrative villages from each town. Finally, approximately 23 households were randomly chosen in each village for face-to-face interviews. In total, 1073 household samples were collected. After excluding incomplete or invalid responses, 1,037 valid questionnaires were retained, yielding an effective response rate of 96.64%.

Variables and description. The primary dependent variable in this study is the well-being of rural residents, which is conceptualized along two dimensions: subjective (internal) and objective (external) well-being. Subjective well-being refers to individuals' personal evaluations and perceptions of life satisfaction, while objective well-being captures assessments of broader societal and material conditions (Alatartseva and Barysheva, 2015). Together, these dimensions reflect individuals' life values and are widely regarded as essential indicators of social progress (Voukelatou et al., 2021). Since the 1980s, non-welfarist approaches have become increasingly influential in the measurement of well-being, emphasizing its multidimensional nature—encompassing not only income and health, but also security, education, and environmental quality (Doyal and Gough, 1984; Nussbaum and Sen, 1993). Following this framework, this study adopts a multidimensional perspective, using happiness and self-rated health as indicators of subjective well-being, and household per capita income as a proxy for objective well-being.

The core explanatory variable in this study is rural residents' internet use. According to the 51st Statistical Report on Internet Development in China, in 2022, 99.8% of Chinese internet users accessed the internet via mobile phones, far exceeding usage rates for desktop computers (34.2%), laptops (32.8%), tablets (28.5%), and televisions (25.9%). This underscores that mobile phones are the dominant device for internet access among Chinese users. Supporting this, Ganju et al. (2016) emphasize that in developing countries, mobile phones serve as crucial tools for enhancing well-being. Accordingly, this study measures internet use by assessing respondents' competence in mobile internet use, which encompasses their overall ability to engage in online social interactions, shopping, entertainment, and information acquisition through mobile devices.

To address potential endogeneity bias, we use the ability to obtain QR codes for epidemic prevention and control as an instrumental variable (IV) for three main reasons. First, during the COVID-19 pandemic, accessing QR codes heavily depended on smartphones and internet connectivity, making this ability strongly correlated with internet use. This satisfies the relevance condition for an IV. Second, the ability to obtain QR codes was primarily determined by government mandates and public health requirements, rather than individual preferences or socioeconomic status, thus fulfilling the exogeneity condition. Third, this variable does not directly affect subjective well-being, self-rated health, or per capita income, but rather influences these outcomes indirectly by facilitating internet use—e.g., increasing interne use frequency, broadening information access, expanding social networks, and enhancing digital skills. Therefore, it also meets the exclusion restriction. In sum, this instrument satisfies the three core requirements of relevance, exogeneity, and exclusivity.

To minimize potential estimation bias due to omitted variables, we follow existing studies (Li et al., 2020; Ma et al., 2020; Lu and Kandilov, 2021) and include a set of control variables at the individual, household, and community levels. At the individual level, we control for gender, age, education level, social status, physical health before age 15, frequency of health-related behaviors, participation in skills training, and the number of insurance types purchased. At the household level, we control for the proportion of non-agricultural labor, per capita cultivated land area, and the level of social support received. At the community level, we control for the quality of local medical and health infrastructure. Furthermore, to control for regional disparities in digital inclusion, county-level fixed effects are included in all regressions. Definitions and descriptive statistics of all variables are reported in Table 1.

Regarding the sample distribution, the average age of household heads exceeds 57 years. In terms of educational attainment, 41.76% of household heads have a primary school education or below, 38.96% have completed junior high school, and 19.29% have attained high school education or above. As shown in Table 1, the mean values of the subjective well-being indicators—happiness and self-rated health—are 3.548 and 3.414, respectively, while the mean of log-transformed household per capita income is 4.134. These results indicate a relatively high level of overall well-being among rural residents. Moreover, the consistency across the three well-being dimensions supports the robustness and reliability of the multidimensional well-being measurement adopted in this study.

Econometric Methodology. This study investigates the impact of internet use on the multidimensional well-being of rural residents. Among the three outcome variables, both happiness and self-rated health are measured on a five-point ordinal scale. Accordingly, we employed an Ordered Probit (Oprobit) model to estimate their associations with internet use. To better isolate the effect of internet use, we included a comprehensive set of control variables at the individual, household, and community levels that may also influence subjective well-being. The empirical specifications are presented as follows:

$$Happiness_i = \alpha_1 Internet_i + \alpha_2 Controls_i + \delta_n + \varepsilon_i \qquad (1)$$

$$Health_i = \beta_1 Internet_i + \beta_2 Controls_i + \delta_n + \varepsilon_i \qquad (2)$$

In these equations, the dependent variables $Happiness_i$ and $Health_i$ represent the self-reported happiness and self-rated health of rural resident i, respectively. The core explanatory variable, $Internet_i$, reflects the level of internet use by individual i, $Controls_i$ denotes a vector of covariates at the individual, household, and community levels, included to mitigate potential endogeneity due to omitted variables. The coefficients α_1, α_2, β_1 and β_2 are parameters to be estimated. δ_n represents county-level fixed effects to account for unobserved regional heterogeneity, and ε_i is the random error term.

Given that household per capita income is a continuous variable, we employed the Ordinary Least Squares (OLS) model to examine the impact of internet use on rural residents' income. The regression specification is as follows:

$$Income_i = c_0 + c_1 Internet_i + c_2 Controls_i + \delta_n + \varepsilon_i \qquad (3)$$

In this equation, the dependent variable $Income_i$ denotes the household per capita income of rural resident i. c_0 is the intercept term, c_1 captures the marginal effect of internet use on income, and c_2 represents the vector of coefficients associated with the control variables. The definitions of the remaining variables and coefficients are consistent with those in Eq. (1).

To address potential endogeneity concerns and assess the validity of the instrumental variable, we conducted tests for weak instruments and under-identification. Given that happiness and self-rated health are ordinal categorical variables, we adopted an instrumental variable probit (IV-Probit) model for their analysis. In contrast, as household per capita income is a continuous variable, we employed the two-stage least squares (2SLS) method to estimate the impact of internet use on income.

For the mechanism analysis, we adopted the Karlson–Holm–Breen (KHB) method, following the approach used in previous studies (Guo et al., 2023; Li et al., 2023). The KHB method is a well-established technique for decomposing

Table 1 Variable selection and description.

Variable Types	Variables	Definition	Mean	SD
Explained variables	Happiness	1=very unhappy; 2=unhappy; 3=moderate; 4=happy; 5=very happy	3.548	0.874
	Self-rated health	1=very unhealthy; 2=unhealthy; 3=moderate; 4=healthy; 5=very healthy	3.414	1.108
	Household per capita income	Log of household per capita income (RMB)	4.134	0.587
Core explanatory variable	Internet use	Ability to engage in online social networking, shopping, entertainment, and information acquisition on mobile phones.: 1=very low; 2=low; 3=moderate; 4=high; 5=very high	3.327	1.595
Instrumental variable	Ability to obtain the QR code for epidemic prevention and control	Whether you can use mobile phone to obtain QR codes for epidemic prevention and control: 1=yes; 0=no	0.643	0.479
Control variables	Gender	1=male; 0=female	0.906	0.291
	Age	Age in years	57.74	11.02
	Educational level	1=primary school and below, 2=junior high school, 3=high school or technical secondary school, 4=college or vocational college, 5=master's degree and above	1.812	0.833
	Social status	1=very low; 2=low; 3=moderate; 4=high; 5=very high	3.205	0.673
	Physical health before age 15	1=very unhealthy; 2=unhealthy; 3=moderate; 4=healthy; 5=very healthy	4.446	0.76
	Frequency of health-related behaviors	Frequency of moderate physical activity and balanced diet: 1=rarely (<1 day), 2=not too often (1–2 days), 3=sometimes (3–4 days), 4=most of the time (5–6 days), 5=always (7 days)	3.642	1.068
	Quality of local medical and health infrastructure	1=very poor; 2=poor; 3=moderate; 4=good; 5=very good	3.636	0.739
	Number of insurance types purchased	Number of the following insurance types purchased (0–5): China New Rural Cooperative Medical Insurance, China New Rural Social Pension Insurance, commercial medical insurance, commercial accident insurance, and commercial property insurance	2.027	0.786
	% of non-agricultural labor	Proportion of non-agricultural labor in household	0.317	0.253
	Cultivated land area per capita	Per capita cultivated land area (mu)	1.155	1.841
	Skills training	Participation in skills training: 1=yes; 0=no	0.241	0.428
	Social support	Number of people willing to provide help: 1=fewer than 3; 2 = 4–5; 3 = 6–7; 4 = 8–9; 5=more than 9	2.329	1.533
Mediating variables	Self-efficacy	Confidence in your ability to improve future standard of living: 1=no confidence; 2=little confidence; 3=moderate confidence; 4=great confidence; 5=very great confidence	3.527	0.966
	Access to health-related information	1=very low; 2=low; 3=moderate; 4=high; 5=very high	2.585	1.433
	Non-agricultural employment opportunities	1=very few; 2=few; 3=moderate; 4=many; 5=very many	2.923	1.152

total effects and testing mediation within regression frameworks. Its core principle involves isolating the component of the mediating variable that is orthogonal to the key independent variable, typically by regressing the mediator on the independent variable and using the residuals in the subsequent model. This approach is particularly appropriate for nonlinear probability models, such as logistic and probit regressions (Smith et al., 2019; Breen et al., 2021; Xue and Liu, 2024).

Results

Baseline regression analysis. Table 2 presents the estimated effects of internet use on the multidimensional well-being of rural residents. Models (1), (3), and (5) examine the associations between internet use and happiness, self-rated health, and household per capita income, respectively, while controlling for a range of individual, household, and community-level variables. Models (2), (4), and (6) additionally account for regional heterogeneity by incorporating county-level fixed effects. Across all model specifications, the coefficients for internet use remain significantly positive at the 5% level, suggesting that greater internet use significantly improves rural residents' well-being—reflected in higher levels of happiness, better self-rated health, and increased household per capita income. These findings provide empirical support for Research Hypothesis 1. Moreover, variables such as educational attainment, perceived social status, and the number of insurance types purchased are positively and significantly associated with well-being outcomes. Age exhibits heterogeneous effects: it is positively related to happiness (coefficient=0.008, $p < 0.05$), but negatively associated with both self-rated health (coefficient = −0.033, $p < 0.01$) and household per capita income (coefficient = −0.003, $p < 0.10$).

Since both happiness and self-rated health are measured as five-point ordinal variables, the coefficients from the baseline regressions capture only the direction and relative strength of their associations with internet use, rather than the precise marginal effects. To improve interpretability, we computed the marginal effects of internet use across different outcome levels, with the results reported in Table3. For happiness, internet use decreases the probabilities of respondents reporting "very unhappy," "unhappy," and "moderate" by 0.3%, 1.3%, and 1.9%, respectively, while increasing the probabilities of reporting "happy" and "very happy" by 1.7% and 1.9%, respectively. A similar pattern is observed for self-rated health: internet use reduces the likelihood of reporting "very unhealthy," "unhealthy," and "moderate" by 0.6%, 2.2%, and 0.6%, respectively, while increasing the likelihood of reporting "healthy" and "very healthy" by 1.2% and 2.1%, respectively.

Endogeneity test. To address potential endogeneity concerns, we conducted tests for weak instruments and under-identification to assess the validity of the chosen instrumental variable. The results indicate that the F-statistic is 426.878, which exceeds the conventional threshold and rejects the null hypothesis of weak instruments. Moreover, the Kleibergen-Paap rk LM statistic is 198.185 ($p < 0.01$),

Table 2 Baseline regression estimation results.

Variables	Happiness		Self-rated health		Household per capita income	
	(1)	(2)	(3)	(4)	(5)	(6)
Internet use	0.095***	0.098***	0.087***	0.099***	0.034***	0.028**
	(0.024)	(0.025)	(0.027)	(0.028)	(0.012)	(0.012)
Gender	0.309***	0.326***	0.068	0.071	−0.018	−0.005
	(0.111)	(0.111)	(0.114)	(0.113)	(0.068)	(0.071)
Age	0.008**	0.008**	−0.033***	−0.033***	−0.003*	−0.003*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)
Educational level	0.079*	0.082*	0.125***	0.132***	0.055***	0.046**
	(0.043)	(0.044)	(0.045)	(0.046)	(0.021)	(0.021)
Social status	0.284***	0.285***	0.110**	0.107*	0.073***	0.076***
	(0.060)	(0.060)	(0.055)	(0.056)	(0.024)	(0.024)
Physical health before age 15	0.086*	0.085*	0.225***	0.236***	0.021	0.012
	(0.048)	(0.049)	(0.046)	(0.046)	(0.029)	(0.028)
Frequency of health-related behaviors	0.070**	0.063*	0.062*	0.069**	0.003	0.003
	(0.034)	(0.035)	(0.033)	(0.034)	(0.019)	(0.019)
Quality of local medical and health infrastructure	0.200***	0.198***	0.203***	0.203***	0.028	0.026
	(0.049)	(0.049)	(0.051)	(0.051)	(0.028)	(0.027)
Number of insurance types purchased	0.174***	0.173***	0.170***	0.144***	0.042*	0.055**
	(0.050)	(0.050)	(0.052)	(0.052)	(0.023)	(0.023)
% of non-agricultural labor	0.189	0.188	0.001	−0.003	0.613***	0.616***
	(0.142)	(0.142)	(0.143)	(0.143)	(0.070)	(0.070)
Cultivated land area per capita	0.017	0.019	−0.005	−0.000	0.019**	0.017*
	(0.014)	(0.014)	(0.016)	(0.016)	(0.010)	(0.009)
Skills training	0.316***	0.303***	0.043	0.048	0.078**	0.077**
	(0.080)	(0.081)	(0.080)	(0.082)	(0.031)	(0.031)
Social support	0.015	0.021	−0.032	−0.025	0.019*	0.017
	(0.022)	(0.022)	(0.022)	(0.023)	(0.011)	(0.011)
Constant term	-	-	-	-	3.313***	3.292***
	-	-	-	-	(0.236)	(0.240)
County-level fixed effects	No	Yes	No	Yes	No	Yes
Observations	1037	1037	1037	1037	1037	1037
R^2	0.070	0.073	0.096	0.099	0.171	0.181

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses and computed using the delta method.

rejecting the null of under-identification. These results confirm the statistical relevance and strength of the instrument. For estimation, we employed the IV-Probit model for the ordinal outcomes (happiness and self-rated health), and used two-stage least squares (2SLS) for the continuous outcome (household per capita income). The results of the instrument validity tests and the corresponding IV estimates are reported in Table 4.

The first-stage results presented in columns (1), (3), and (5) indicate that the estimated coefficient for the instrumental variable—the ability to obtain QR codes for epidemic prevention and control—is 1.749 and statistically significant at the 1% level. This finding confirms that access to mobile-based QR codes substantially increases the likelihood of internet use, thereby validating the instrument's relevance. The second-stage results, reported in columns (2), (4), and (6), show that even after addressing potential endogeneity, internet use remains a significant determinant of well-being. Specifically, the estimated effects of internet use on happiness, self-rated health, and household per capita income are 0.093, 0.098, and 0.057, respectively, all significant at the 5% level. These results reinforce the robustness of the baseline findings and highlight the positive influence of internet use on the multi-dimensional well-being of rural residents.

Mechanism analysis. The preceding empirical results confirm that internet use exerts a significant positive impact on the well-being of rural residents. However, the underlying mechanisms through which this effect is realized warrant further investigation. To explore these pathways, we adopt the Karlson–Holm–Breen (KHB) method to assess the mediating roles of self-efficacy, access to health-related information, and non-agricultural employment opportunities in the relationship between internet use and multidimensional well-being.

Table 5 reports the results of the mediation analysis. The estimated indirect effects of self-efficacy (0.012), access to health-related information (0.032), and non-agricultural employment opportunities (0.010) are all statistically significant at the 5%, 5%, and 1% levels, respectively. These results confirm that each of the three factors serves as a significant mediator, thereby lending

Table 3 The marginal effects of the Oprobit model.

Variables	Y = 1	Y = 2	Y = 3	Y = 4	Y = 5
Internet use	Happiness				
	−0.003***	−0.013***	−0.019***	0.017***	0.019***
	(0.001)	(0.004)	(0.005)	(0.004)	(0.005)
	Self-rated health				
	−0.006***	−0.022***	−0.006***	0.012***	0.021***
	(0.002)	(0.006)	(0.002)	(0.003)	(0.006)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled
County-level fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1037	1037	1037	1037	1037

Note: *** indicates significance at the 1% level. Standard errors are reported in parentheses and computed using the delta method.

Table 4 Instrumental Variable Tests and Regression Results.

Variables	(1) Internet use	(2) Happiness	(3) Internet use	(4) Self-rated health	(5) Internet use	(6) Household per capita income
Internet use		0.093**		0.098**		0.057**
		(0.047)		(0.042)		(0.023)
Ability to obtain the QR code for epidemic prevention and control	1.749*** (0.084)		1.749*** (0.084)		1.749*** (0.085)	
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
County-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	426.878					
Kleibergen-Paap rk LM statistic	198.185***					
Observations	1037	1037	1037	1037	1037	1037

Note: *** and ** indicate significance at the 1% and 5% levels, respectively. Standard errors are reported in parentheses and computed using the delta method.

Table 5 Mediation effect test based on the KHB method.

Mediation Pathway	Indirect Effect	Bootstrap standard error	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)
Internet use → Self-efficacy → Happiness	0.012**	0.005	0.003	0.022
Internet use → Access to health-related information → Self-rated health	0.032**	0.013	0.007	0.056
Internet use → Non-agricultural employment opportunities → Household per capita income	0.010***	0.003	0.004	0.016

Note: *** and ** indicate significance at the 1% and 5% levels, respectively.

Table 6 The impact of internet use on multidimensional well-being: age heterogeneity.

Variables	Happiness		Self-rated health		Household per capita income	
	Young & middle-aged	The elderly	Young & middle-aged	The elderly	Young & middle-aged	The elderly
Internet use	0.109***	0.093***	0.119***	0.063	0.044***	0.009
	(0.036)	(0.035)	(0.040)	(0.039)	(0.017)	(0.018)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
County-level fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	625	412	625	412	625	412
R^2	0.078	0.097	0.096	0.056	0.189	0.165

Note: *** indicates significance at the 1% level. Standard errors are reported in parentheses and computed using the delta method.

Table 7 Mean values of multidimensional well-being at different levels of internet use.

Internet use level	Happiness			Self-rated health			Household per capita income		
	Overall	Y&M	E	Overall	Y&M	E	Overall	Y&M	E
Very low	3.363	3.304	3.382	2.916	3.179	2.829	3.978	3.999	3.971
Low	3.416	3.279	3.551	3.248	3.324	3.174	3.971	3.917	4.025
Moderate	3.504	3.500	3.510	3.363	3.488	3.143	4.119	4.163	4.040
High	3.393	3.354	3.471	3.280	3.455	2.941	4.117	4.199	3.956
Very high	3.776	3.763	3.836	3.830	3.965	3.247	4.294	4.312	4.215
Mean	3.548	3.568	3.517	3.414	3.678	3.012	4.134	4.203	4.029
Observations	1037	625	412	1037	625	412	1037	625	412

Note: Y&M Young and middle-aged rural residents, E Elderly rural residents.

empirical support to Hypotheses 2, 3, and 4. Overall, internet use enhances happiness by strengthening self-efficacy, improves self-rated health through better access to health-related information, and increases household per capita income by expanding non-agricultural employment opportunities.

Heterogeneity analysis. To gain deeper insights into the relationship between internet use and the well-being of rural residents, this section explores the heterogeneous effects across different demographic groups. Specifically, we aim to answer the question: who benefits more from internet use in terms of well-being? Baseline regression results indicate that age plays a nuanced role—being positively associated with happiness but negatively correlated with self-rated health and household per capita income. To further examine these heterogeneous effects, we conducted subsample regression analyses by dividing the sample into two groups based on age: individuals aged 60 and below (young and middle-aged rural residents) and those above 60 (elderly rural residents).

As shown in Table 6, after controlling for relevant covariates and regional fixed effects, internet use significantly enhances all three dimensions of well-being—happiness, self-rated health, and household per capita income—among young and middle-aged rural residents. The estimated coefficients are 0.109, 0.119, and 0.044, respectively, all statistically significant at the 1% level. These results underscore the important role of internet use in improving the multidimensional well-being of this demographic group. In contrast, among elderly rural residents, internet use exerts a significant positive effect only on happiness (coefficient=0.093, $p < 0.01$), while its effects on self-rated health and household per capita income are not statistically significant. This pattern suggests that younger rural residents benefit more from internet use in terms of well-being compared to their older counterparts.

To further examine variations in multidimensional well-being among rural residents with differing levels of internet use, we categorized internet use intensity into five groups: very low, low, moderate, high, and very high (see Table 7). The results indicate that as internet use intensity increases, rural residents generally experience improvements in happiness, self-rated health, and household per capita income. Furthermore, across all levels of internet use, the young and middle-aged group consistently exhibits higher average well-being scores than the elderly group in all dimensions.

Specifically, the young and middle-aged group's average happiness score is 3.568, which is 0.051 points higher than the elderly group's 3.517. The disparity is more pronounced for self-rated health, where the young and middle-aged average 3.678 compared to 3.012 among the elderly—a gap of 0.666 points. Regarding household per capita income, the younger cohort also leads, with a mean of 4.203 versus 4.029 for the elderly, a difference of 0.174 points. These findings indicate that the elderly population faces greater challenges across multiple dimensions of well-being, with the most substantial gap observed in self-rated health, followed by income and happiness.

Discussion

This study extends Sen's Capability Approach into the digital domain by constructing a comprehensive analytical framework—"psychology–health–economy"—to examine how internet use influences the well-being of rural residents. The findings demonstrate that internet use significantly enhances rural residents' happiness. The internet contributes to breaking the vicious cycle of poverty and limited personal agency by enhancing individuals' self-efficacy, especially in areas such as online social interaction and self-directed learning. This result is consistent with previous studies (Li et al., 2014; Zheng et al., 2016). Moreover, improved access to health-related information via the internet promotes healthier behaviors among rural residents, such as disease prevention and physical exercise (Li et al., 2020; Ghweeba et al., 2022). In the economic dimension, internet use facilitates engagement in e-commerce and entrepreneurship, which have been identified as key drivers of income improvement (Chao et al., 2021; Zhang et al., 2023). These findings suggest that strengthening digital capabilities among rural populations can lower transaction costs and improve access to markets and resources, particularly in underdeveloped regions constrained by geographic and infrastructural barriers. This highlights the importance of designing poverty alleviation strategies that go beyond traditional economic measures, focusing instead on expanding digital infrastructure, improving accessibility and usability of internet technologies, and optimizing digital application scenarios tailored to local needs.

We also find significant heterogeneity across age cohorts: the well-being benefits of internet use are markedly greater for individuals aged 60 and below compared to their older counterparts. This disparity can be attributed to three key factors. First, differences in psychological adaptation to technology. Due to the threshold effect of digital skills, older adults are more likely to be constrained by technological anxiety (Zhou et al. 2023; An et al. 2024), which undermines their psychological empowerment. Second, differences in health behaviors. Limited digital literacy and privacy concerns cause older adults to rely more on traditional sources of health information (Taha et al., 2009), thereby weakening the internet's effect in promoting healthy behaviors (Hale et al., 2010). Third, barriers to economic participation. Technological complexity and age-related cognitive decline restrict older adults from engaging in online employment opportunities, resulting in a weaker income effect from internet use. This suggests that digital services should prioritize inclusive design by developing user-friendly interfaces and leveraging tools such as short-form videos and generative AI to enhance digital literacy and engagement among older adults.

This study proposes a hierarchical "infrastructure–capability–service" strategy to promote well-being in less developed regions through digital empowerment. First, priority should be given to strengthening digital infrastructure. Targeted interventions may include expanding internet coverage in remote areas using low-orbit satellites and mobile stations, establishing county-level cloud data platforms to integrate key public service, agricultural, and healthcare datasets, and narrowing the digital access gap. Second, it is essential to foster the digital capabilities of rural residents. Drawing on international best practices—such as the UK's Digital Skills for the 3rd Age program—a stratified digital literacy training system should be developed. For younger cohorts, training in e-commerce operations, livestream marketing, and digital entrepreneurship can enhance engagement in the digital economy. For older adults, age-friendly education programs focused on using essential applications (e.g., telemedicine platforms and government service portals) can help overcome digital exclusion and improve quality of life. Third, service delivery should be optimized to transform the "technological dividend" into a tangible "well-being dividend." This entails the development of smart agriculture platforms that integrate IoT-based environmental monitoring and AI-driven decision support systems to promote precision farming and improve agricultural productivity. It also involves expanding digital health platforms to support telemedicine services, chronic disease management, and personalized health interventions, with particular attention to the needs of elderly populations. Furthermore, efforts should focus on building an inclusive rural e-commerce ecosystem by establishing county-level e-commerce incubation centers, offering integrated services such as logistics support, product branding, and digital marketing. These initiatives aim to unlock the multifunctional potential of agriculture and result in tangible economic gains for rural communities.

This study is subject to several limitations. First, although it utilizes cross-sectional data collected from previously impoverished regions and employs rigorous techniques—such as instrumental variable estimation—to mitigate endogeneity concerns, the analysis remains constrained in capturing the dynamic and long-term impacts of internet use on multidimensional well-being. Future research should consider constructing panel datasets for longitudinal tracking or applying a combination of analytical methods to enable cross-validation of findings. Second, while the study focuses on the positive contributions of internet use to individual well-being, it does not account for potential negative externalities. For instance, internet addiction—documented across various age cohorts—may erode mental health and offset the benefits associated with digital engagement. Future investigations should broaden the conceptualization of digital well-being to encompass both its enabling and detrimental aspects. Third, despite the adoption of a stratified sampling strategy to enhance sample representativeness, two potential sources of bias merit attention: (1) Geographic stratification may obscure intra-stratum heterogeneity in digital engagement—such as the coexistence of digitally advanced e-commerce demonstration villages and traditional agricultural communities within the same administrative region; and (2) Non-response bias, particularly prevalent in areas with high topographical gradients or among elderly populations, may compromise data accuracy. To address these limitations, future studies could integrate mobile signaling data with longitudinal field surveys to establish a dynamic, multi-layered sampling framework that enhances the precision and robustness of empirical estimations.

Conclusion

This study examines the impact of internet use on the multidimensional well-being of rural residents, based on survey data from 1,037 households in previously impoverished regions of China. This study moves beyond income-centric views by adopting a "psychology–health–economy" framework to offer a more holistic understanding of digital inclusion in the post-poverty era. The findings reveal that internet use significantly improves happiness, self-rated health, and household income. These effects are primarily mediated through enhanced self-efficacy, greater access to health-related information, and increased non-agricultural employment opportunities. Notably, the well-being benefits are more pronounced among younger and middle-aged individuals, revealing critical age-based disparities in the benefits of digital engagement. These results underscore the transformative potential of digital technologies in expanding individual capabilities and driving rural revitalization. In response, the study advocates for a targeted "infrastructure–capability–service" strategy aimed at promoting equitable digital access, fostering meaningful engagement, and supporting sustainable development in rural areas.

Data Availability

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Author contributions
YS and WJL conceived and designed the study. Data were collected by YS, WJL, and FBH. YS and WJL conducted the analysis and interpretation. The manuscript was drafted by YS and WJL, and critically revised by YS, WJL, and FBH. All authors have read and approved the final version for publication.

Competing interests
The authors declare no competing interests.

Ethical approval
This study was conducted in accordance with the ethical standards of the Declaration of Helsinki and its later amendments or comparable ethical standards. Ethical approval was obtained from the Scientific Ethics Committee of Huazhong Agricultural University (Approval No. HZAUHU-2022-0027) on July 10, 2022. The Scientific Ethics Committee of Huazhong Agricultural University operates independently and complies with internationally recognized standards for ethical oversight. The written informed consent form was reviewed and approved by the committee prior to any contact with participants or data collection.

Informed Consent
After receiving ethical approval on July 10, 2022, members of the research team conducted fieldwork from July 13 to July 30, 2022, in Jianshi County, Xianfeng County, Yunxi County, Yunyang District (formerly Yun County), and Xiaochang County. The study complied with all relevant local laws and institutional policies in the regions where the fieldwork was conducted. Before each questionnaire-based interview, participants were provided with a clear explanation of the study's purpose, procedures, and content, both verbally and through the cover page of the questionnaire. Written informed consent was obtained from all participants on the same day, immediately before each interview. Participants were explicitly informed of their right to withdraw from the study at any time without penalty. Consent forms were physically attached to the completed paper questionnaires and securely stored. Paper records will be retained for five years, while electronic data will be stored indefinitely on encrypted servers. All participant data were anonymized to protect privacy and ensure confidentiality. Data are stored in digital format, with access limited to the principal investigator and authorized members of the research team. Any future requests for data access will be reviewed and approved internally by the research team. This study did not involve any vulnerable populations. All participants voluntarily agreed to participate and consented to the use of their data for academic research purposes. A compensation of 10 RMB was provided to each participant upon completion of the entire survey and questionnaire.

Additional information
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