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<https://doi.org/10.1057/s41599-024-02645-x>

OPEN

Breaking the chains of poverty: examining the influence of smartphone usage on multidimensional poverty in rural settings

Xian Liang^{1,4}, Hui Xiao ^{1,4}, Fangmiao Hou¹, Xuan Guo², Lishan Li² & Longjunjiang Huang³✉

We analyze the impact of smartphone usage on multidimensional poverty reduction. Utilizing the A-F approach, we compute a multidimensional poverty index based on five dimensions: education, health, income, living standard, and labor force. This index categorizes multidimensional poverty into three levels: Vulnerable Multidimensional Poverty Index (*VMPI*), General Multidimensional Poverty Index (*GMPI*), and Extreme Multidimensional Poverty Index (*EMPI*), following MPI criteria. Furthermore, we investigate the mediating role of social capital in the smartphone-multidimensional poverty relationship through a mediating effects analysis. We used the survey data of 382 sample out-of-poverty rural households in Jiangxi, China, in 2020. Our results indicated that: (1) Education (37.80%), labor force (29.7%), and health (20.40%) were identified as the primary contributors to multidimensional poverty. (2) Increasing deprivation categories correlated with declining multidimensional poverty index, following an inverted U-shaped pattern. (3) Smartphone usage significantly reduced *VMPI* (57.6%), *GMPI* (52.6%), and *EMPI* (5%). (4) Social capital fully mediated *EMPI* reduction through smartphones (91.67%), and partially mediated *VMPI* (14.09%) and *GMPI* (20.84%) reduction. These insights inform targeted policy formulation for rural multidimensional poverty reduction.

¹School of Economics and Management, Beijing Forestry University, 100083 Beijing, China. ²School of Economics and Management, Jiangxi Agricultural University, 30041 Nanchang, China. ³School of Business Administration, Zhongnan University of Economics and Law, 430073 Wuhan, China. ⁴These authors contributed equally: Xian Liang, Hui Xiao. ✉email: huanglongjunjiang@stu.zuel.edu.cn

Introduction

According to the information presented in a white paper released by the State Council in 2021, China successfully accomplished the task of eradicating absolute poverty by the end of December 2020. As a result, poverty management in China has transitioned from a focus on absolute poverty to relative poverty¹. Research studies have revealed that 11.34% of rural households that have surpassed the income-based poverty threshold have also experienced relief from multidimensional poverty (Liu and Xu, 2016). This indicates that rural poverty represents a complex and diverse real-world challenge. Sen (1976) introduced a distinct criterion that deviates from the traditional use of “low income” as the sole indicator of poverty. It involves identifying poverty across multiple dimensions, including education, health, and living standards. Alkire and Foster (2011), researchers from the Centre for Poverty and Human Development Research at the University of Oxford, UK, presented the pioneering analytical model of multidimensional poverty in their publication “Counting and Measuring Multidimensional Poverty.”² In recent years, the Internet has witnessed widespread adoption and has gradually become an indispensable component of people’s daily lives. According to data released in the China Rural Revitalization Comprehensive Survey Report 2021, nearly 20 percent of villages nationwide have achieved “home access” to broadband, and more than 90 percent of rural households own at least one smartphone³ (“China Rural Revitalization Comprehensive Survey Report 2021”, 2022). The Chinese government has emphasized its role and issued a series of crucial directives and instructions to facilitate the implementation of online poverty alleviation initiatives. In the context of poverty alleviation governance, the use of smartphones as a tool for Internet use offers new opportunities to address these challenges.

There is ongoing debate among academics regarding the extent to which smartphone usage, can significantly contribute to poverty alleviation. On one hand, some scholars argue that the widespread availability and high penetration of smartphone usage can effectively reduce rural poverty. They argue that the use of smartphones can significantly increase farmers’ incomes by overcoming spatial and temporal barriers to market information, facilitating cost-effective transactions, and enabling farmers to benefit from market expansion (Zhuo et al., 2023). Research suggests that smartphone usage can lead to a significant 25–30% increase in individual supplementary wage income (Van and Van, 2009; Panteli et al., 2019). Moreover, it actively promotes job search efforts, enhances the likelihood of non-farm employment (Zeng et al., 2023), facilitates entrepreneurial opportunities (Mack et al., 2017), expedites the dissemination of agricultural information, improves the income structure of farming households, and enhances the well-being of migrant workers (Aker et al., 2016). Liu et al. have concluded that the utilization of digital information technology enhances social capital in terms of social networks, social participation, and social trust, subsequently alleviating multidimensional poverty (Liu et al., 2021), social capital can help alleviate informal financial constraints rooted in interpersonal relationships, thereby addressing the multidimensional aspects of rural poverty (Xiong et al., 2021). Furthermore, Wang et al. have demonstrated a significant correlation between social capital and a reduced likelihood of multidimensional poverty among rural households (Wang et al., 2023).

On the other hand, some scholars believe that smartphone use may exacerbate the “digital divide”, thereby hindering income growth for vulnerable and poor groups (Tayo et al., 2016). With the continuous advancement of information technology, the digital divide between economically developed areas and poor rural areas, between traditional small farmers and new agricultural operators, and between urban and rural areas is becoming more and more difficult to overcome (Acilar, 2011).

Limited access to IT facilities in rural areas and inadequate digital literacy prevent most producers, especially those in poor rural areas, from benefiting from the digital dividend and increasing their income through the use of information technology (Deichmann et al., 2016). Notably, these contrasting perspectives highlight the complexity of the relationship between smartphone use and poverty alleviation. Further research and analysis are needed to fully understand the multifaceted impact of smartphone use on poverty reduction.

The purpose of this paper is to sort out the complex relationship between smartphone use and multidimensional poverty. Perspectives and findings of the existing body of literature provide a solid research foundation for the present study. Based on the widespread use of smartphones in China, our research aims to extend the existing literature in the following ways. Firstly, we expand the multidimensional poverty indicator system by incorporating income and labor dimensions based on the criteria for poverty eradication among poor households in China. We classify multidimensional poverty into vulnerable, general, and extreme categories, thereby constructing a comprehensive multidimensional indicator system tailored to households transitioning out of poverty, enriching the research perspective on measuring multidimensional poverty in China. Secondly, we adopt smartphone usage as a focal point to analyze the influencing factors of farmers’ multidimensional poverty. This approach contributes to the existing research on internet poverty alleviation and further enhances our understanding of the interplay between smartphone use and poverty in rural contexts. Thirdly, most existing studies have examined the relationship between smartphone usage, social capital, and poverty from singular perspectives. By measuring social networks, social trust, social participation, and social support to construct a comprehensive social capital index, we empirically explore the mediating role of social capital in the impact and mechanism of smartphone usage on multidimensional relative poverty among rural households. This holistic approach enhances our understanding of the intricate dynamics between smartphone usage, social capital, and multidimensional poverty.

The remainder of this paper is organized as follows: Part “Analytical framework and assumptions” presents the theoretical analysis and research hypotheses. Part “Methods” describes the research design and data sources employed. Part “Results” empirically examines the effects of smartphone usage on multidimensional poverty, supplemented by robustness tests, and an empirical test of the theoretical mechanisms. Part “Discussion” is the discussion of the paper. Part “Conclusions” is the conclusion of the paper.

Analytical framework and assumptions

Impact of smartphone usage on multidimensional poverty. Internet use can help reduce information asymmetry as it disseminates information fast and at a low cost. Due to the popularization of the Internet in rural China, smartphone usage has become an essential part of rural residents’ lives and work (Nie et al., 2021). The focus on smartphones is important because their penetration continues to increase among the farming communities, and because they provide more advanced communication services (Ma et al., 2020). Presently, smartphones serve as the primary means of accessing the Internet in rural communities. It is worth noting that rural households that have transitioned out of poverty, predominantly comprising middle-aged and elderly individuals, may encounter barriers due to lower literacy and cognitive abilities, posing challenges to their effective use of smartphones. However, if the information technology proficiency of this demographic can be effectively enhanced and their smartphones can be fully utilized in their daily activities, it is

expected to play a significant role in fostering social integration among impoverished households and consequently alleviate their multidimensional poverty. The substantial impact of smartphone usage on the lives of residents has been well-documented in academic literature (Yang et al., 2021). In terms of research focus, while scholars have primarily examined the effects of smartphone usage on income, employment, rural finance, and well-being (Ma and Wang, 2020), there remains a gap in exploring its potential for alleviating multidimensional poverty.

Drawing upon the existing body of research, we posit that smartphone use behavior can significantly impact the multi-dimensional poverty status of households that have recently emerged from poverty. By utilizing smartphones, these households can mitigate the time costs associated with accessing favorable information (Ma and Wang, 2020). Such information includes but is not limited to e-commerce platform matching, employment opportunities, technical services for agricultural machinery, and financial advisory services. The availability of these resources can expedite the adaptation process of households emerging from poverty to their local communities while fulfilling their employment and livelihood needs (Xiao et al., 2022a, 2022b, 2022c). Consequently, these households can gain access to essential technical information, enhance employment stability, and seek financial support, thereby facilitating multidimensional poverty alleviation. It is important to note that a significant contributing factor to falling into multidimensional poverty is the scarcity of abundant information resources. By harnessing smartphones, households emerging from poverty can acquire an array of socio-economic resources necessary for their transformation, making smartphone devices a vital medium through which these households can search for information and integrate resources (Mesch and Talmud, 2011).

Figure 1 presents a comprehensive framework depicting the mechanisms through which smartphone use contributes to the alleviation of multidimensional poverty, ultimately fostering sustainable development. The utilization of smartphones yields significant benefits in two key ways.

Firstly, smartphone usage directly mitigates the costs associated with information acquisition for farmers (Kim et al., 2018). Within the traditional intermediary-based trading model, multiple transactional layers exist between the procurement and sale of agricultural products. Moreover, middleman buyers exploit their

information monopoly to suppress purchase prices while inflating sale prices, resulting in substantial profits at the expense of farmers' interests. By leveraging smartphones, farmers can access transparent information on agricultural products through diverse channels, such as the Internet. This enables direct matching between buyers and sellers, effectively circumventing the exploitative price differentials orchestrated by intermediaries. Particularly for farmers, the utilization of Smartphone usage tools assumes a pivotal role in disrupting their low-level equilibrium, surmounting their information predicament, and enhancing their information access. Smartphone usage serves as an efficacious means to surmount information barriers, empowering farmers in their journey toward multidimensional poverty alleviation.

Secondly, the utilization of smartphones contributes to the expansion of farmers' market participation. Compared to traditional information technology, the advent of smartphones has a pronounced impact on reducing information costs and surmounting information barriers for farmers (Khanal et al., 2015). Notably, it has a more substantial effect in broadening farmers' market engagement. On one hand, the diffusion function of information technology, facilitated by smartphones as a specific new media within the realm of smartphone usage, serves to transform the disadvantaged position of agricultural products within the supply chain. Through the utilization of smartphone usage, individual farmers, positioned at the lowermost end of the production and manufacturing chain, can internalize marketing and after-sales processes. On the other hand, smartphone usage enables the seamless expansion of agricultural products from provincial to national and even international markets, effectively acting as a conduit for connecting diverse markets. As the scope of interconnected markets facilitated by smartphone usage expands, so too do the opportunities for farmers to establish connections with other markets.

Hence, based on the aforementioned theoretical analysis, we propose Hypothesis 1:

Hypothesis 1: Smartphone usage can alleviate multidimensional poverty in rural households. However, as the criteria for identifying multidimensional poverty become increasingly stringent, the role of smartphones in poverty alleviation gradually diminishes.

The mediating role of social capital. In terms of rural household income, scholars have recognized smartphones as a powerful tool

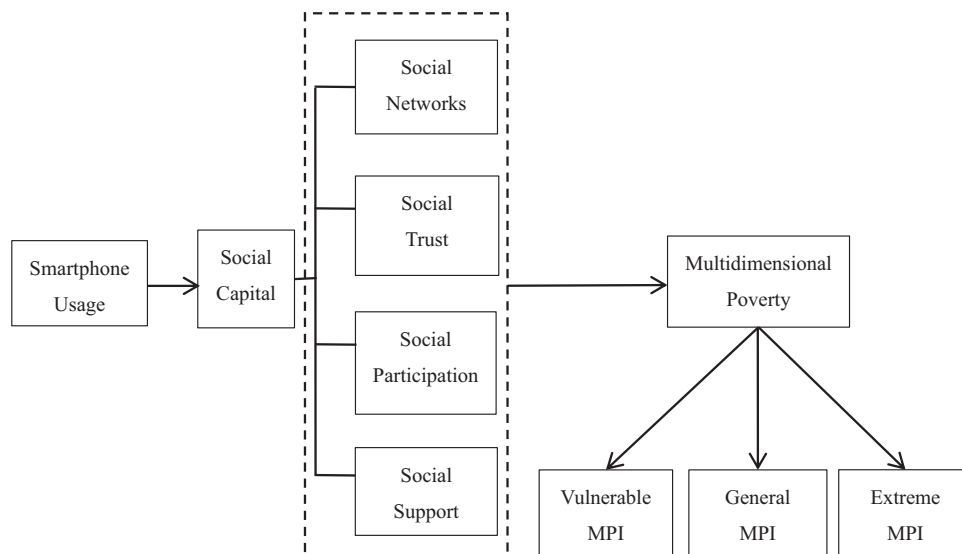


Fig. 1 The mechanisms of smartphone usage and multidimensional poverty alleviation. Arrows indicate the direction of flow of a process, solid lines indicate the variables discussed in this paper, and dashed lines indicate the sub-variables that make up the variables chosen for this paper.

for enhancing human capital and expanding social capital, attributing them to the potential income-enhancing effect (Ma and Wang, 2020). However, multidimensional poverty encompasses more than just the income level of rural households; it considers various aspects such as rural households' capacity expansion, access to education, and social security (Gong et al., 2020). Within this context, social capital, as an informal form of capital, serves as a sustainable network of relationships that provides risk protection and assistance to rural households within their social networks (Kaila and Tarp, 2019). Particularly for multidimensionally poor households, social capital plays a crucial role in facilitating information exchange, and resource provision, reducing transaction costs, enabling transactions, and ultimately alleviating poverty.

Households trapped in multidimensional poverty face not only a lack of adequate capital and capacity to mitigate risks but also a dearth of protection from formal systems. In cases where health shocks result in medical expenses surpassing the household's ability to pay, this group heavily relies on social capital in the form of informal social networks to address such challenges (Duke and Montag, 2017). Functioning as a resource embedded within an individual's social network, social capital enables connections and access to diverse forms of resources through direct or indirect relationships. It offers valuable information, fosters trust, provides emotional support, and facilitates economic transactions for individuals (Klasen and Waibel, 2015). In the context of improving physical living conditions, the expansion of social capital can enhance cooperation among farming households, thereby improving the rural employment structure. Similarly, in the context of enhanced employment structures, the expansion of social networks and the strengthening of social capital can alleviate credit constraints faced by multidimensionally poor households, enabling them to access sufficient physical capital for entrepreneurial activities. This, in turn, reduces income disparities and alleviates multidimensional poverty within these households (Blank and Groselj, 2014).

The growth and enrichment of social capital can mitigate uncertainty and transaction costs for multidimensionally poor households, enabling appropriate investments in human and physical capital (Chaudhuri et al., 2005). Social platforms such as WeChat and Jitterbug have played a significant role in helping farmers broaden their social networks and maintain strong social ties (Zhu et al., 2022). The presence of robust social capital allows rural households to access resources that mitigate risks, ultimately improving household welfare and alleviating poverty. This is particularly evident within the context of the dual system of rural finance, where social capital serves as a means to alleviate informal financial constraints based on interpersonal relationships and address multidimensional poverty among rural households (Banerjee and Jackson, 2017).

Hypothesis 2: Smartphone usage alleviates multidimensional poverty in rural households by exerting its influence on the mediating role of social capital.

Methods

Jiangxi Province, located between latitudes 24°29'14" and 30°04'43" north and longitudes 113°34'18" to 118°28'56" east, is renowned as a traditional agricultural region and a significant grain-producing area in China. Moreover, it plays a crucial role in the nationwide poverty alleviation efforts. As of June 2020, Jiangxi comprised 61 counties, 12 county-level cities, 27 municipal districts, 61 municipalities, and a total of 100 county-level divisions. Among them, 58 counties (including cities and districts) were identified as former Central Soviet Union regions and areas facing special hardships, highlighting their significance as

key regions in the battle against poverty. In terms of economic indicators, Jiangxi Province's gross regional product reached 2569.150 billion yuan in 2020 and increased to 2961.97 billion yuan by 2021. The population residing in Jiangxi Province at the end of 2021 stood at 45.1740 million.

Fieldwork was conducted by the research team in five selected counties and districts within Jiangxi Province from July to August 2020. These areas encompass Anyi County, Jinxian County, Nanchang County, Wanli District, and Xinjian District. To ensure comprehensive data collection, the research team, consisting of master's and doctoral students from Jiangxi Agricultural University, collaborated with faculty members to design the questionnaire and determine the research subjects. These chosen research sites are recognized as traditional agricultural regions and are crucial focal points for poverty eradication efforts in Jiangxi Province, making them representative areas for our research.

The study employed a combination of questionnaires and field interviews. Prior to the survey, the project lead conducted a five-day interview training session for the interviewers. The sample villages were selected using a stratified sampling approach, employing a combination of point and surface sampling techniques. Firstly, five counties and districts were selected based on their agricultural resources and the income levels of rural households. Subsequently, eight villages were chosen within each county and district, and finally, ten households that had successfully overcome poverty were randomly selected in each village. Questionnaires and structured interviews were conducted with each rural household, focusing on information related to household production, livelihood, and basic village characteristics. The questionnaire covered three main categories: (1) demographics of rural households (such as age, gender, education, health, income, and marital status); (2) household capital (including social capital, human capital, furniture capital, and housing capital); and (3) household livelihood strategies (including energy use, income sources, consumption sources, agricultural operations, and non-agricultural activities).

After excluding 18 surveys with missing crucial variables, a total of 382 valid questionnaires were obtained from the 400 initially collected. This yields a sample validity rate of 95.5%.

Variable selection

Dependent variable. The present study focuses on multidimensional poverty as the dependent variable. However, it is important to note that there is no standardized criterion for identifying the dimensions and indicators of multidimensional poverty due to regional variations in climate, culture, and consumption patterns. To establish a foundation for this research, the Multidimensional Poverty Index (MPI) recommended under the Sustainable Development Goals (SDGs) framework was adopted (Alkire and Jahan, 2018). Furthermore, the Oxford Poverty and Human Development Initiative (OPHI) provides a comprehensive and well-established measurement system, particularly in relation to the MPI index. In 2010, the United Nations Development Program (UNDP) published the Multidimensional Poverty Index (MPI) for 104 countries and territories worldwide in the Human Development Report. The MPI represents a further refinement of the Human Poverty Index (HPI) and the Human Development Index (HDI). It serves as a tool to gauge the extent of poverty experienced by individuals or households across different dimensions. A smaller MPI value indicates a lower level of poverty for the individual, while a higher value signifies a higher level of poverty.

The MPI encompasses three broad dimensions: education, health, and living standards. The dimension of education consists of two indicators: schooling and attendance. The health

dimension comprises two indicators: nutrition and mortality. Lastly, the living standards dimension encompasses six indicators: electricity, sanitation, water, floor quality, cooking fuel, and assets. In total, there are ten indicators considered within the MPI.

According to the Outline of Poverty Alleviation and Development in Rural China (2011–2020), poverty reduction targets should aim to ensure individuals can meet their basic needs, including food, clothing, compulsory education, basic healthcare, and housing. Drawing upon the existing literature (Cao et al., 2023), the United Nations Millennium Development Goals (MDGs), China's poverty alleviation policies and goals, as well as data availability, this study argues that income and labor force should also be considered when selecting relative poverty metrics. Therefore, the research selects ten indicators across five dimensions: health, education, income, living standards, and labor force. The chosen dimensions and their respective indicators are as follows:

Health: In the health dimension, two indicators were utilized: medical expenses and health insurance. It is worth noting that the average health insurance coverage rate for rural residents in China stands at 60%, with precise reimbursement rates varying across provinces and cities. The Chinese government recognizes the significance of extending health insurance coverage to rural areas as part of its poverty reduction efforts.

The indicators related to the physical health of farmers include their medical visit costs, which serve as a reflection of their health status. Moreover, these indicators play a crucial role in assessing the effectiveness of government policies aimed at poverty reduction, as membership in health insurance programs reduces the farmers' out-of-pocket payment burden. Indicators of the physical health of the farmers can be found in their medical visit costs, but they can also be used to determine how well the government is doing in reducing poverty because health insurance membership lowers the farmers' own payment ratio. A member of the household who incurs medical costs due to a major illness or hospitalization is regarded to be lacking the medical expenditure indicator (Mondal et al., 2010). Likewise, a member of the household who lacks medical insurance in rural areas is deemed to be lacking the medical insurance indicator (Xiao et al., 2022a, 2022b, 2022c).

Education: In the education dimension, one indicator was employed: years of education. The indicator of education years serves as a measure of deprivation for household members aged 16 and above who have received less than 9 years of formal education.

Income: In the income dimension, the primary indicator utilized is the per capita disposable income of rural households. Income serves as a crucial measure for assessing the poverty status of rural households, providing valuable insights into their economic well-being. The threshold value for rural households' income in this paper was determined as a percentage of the median disposable income of rural inhabitants, which was set at 40% of the median per capita disposable income of rural residents nationwide (Xin et al., 2016), rather than using the absolute poverty line as the standard. The per capita disposable income of rural households below 40% of the 2019 national median disposable income per rural resident (5755.6 yuan) is considered deprived of the per capita disposable income indicator.

Living Standard: The standard of living dimension comprises five indicators: electricity, cooking fuel, floor, assets, and per capita housing area (Aguilar and Sumner, 2020). The indication of electricity is said to be deprived if the family is without electricity.

The cooking fuel indicator is deprived if the primary fuel for cooking is unclean fuel, such as firewood. The floor indicator is deemed to be deprived if the structure is made of mud. The assets indicator is deemed to be deprived if households do not own more than one of the following assets: battery car, car, television, refrigerator, washing machine, telephone, air conditioner, computer, electric heater, or water heater. Less than 12 square meters is seen as a sign of deprivation in terms of housing area per capita.

Labor: The "13th Five-Year Plan," which was released by the State Council at the end of 2016, underscores the importance of establishing a robust employment system as a means to uplift the impoverished population from poverty to prosperity. Recognizing the unique composition of each household, this study primarily focuses on the labor force's proportion within the population, as it serves as a critical determinant of living standards and a key pathway to breaking the cycle of poverty.

The State Council emphasizes the imperative to "ensure that impoverished households with available labor force have at least one employed member." Considering that this research is conducted at the household level, it is essential to consider the average rural household size in China, which stood at 3.1 individuals in 2018. Consequently, a labor force ratio of less than one-third is regarded as indicative of a shortage in labor indicators (Elsby et al., 2015).

The selection of indicator weights in current research lacks consensus, and drawing upon the analytical framework of the Global Multidimensional Poverty Index (GMPI), this study adopts the equal-weight method, assigning equal weights to both dimensions and indicators. The analysis encompasses 10 indicators across 5 dimensions, namely health, education, income, living standard, and labor force. Each dimension carries a total weight of 1/5, ensuring equal emphasis on all dimensions. Similarly, within each dimension, the weights assigned to individual indicators are also equal, following a ratio of 1/5, 1/10, or 1/25. Detailed information regarding the threshold values and weight settings for each index can be found in Table 1. To identify multidimensional poverty, the annual cumulative value of each dimension index for the surveyed farmers must exceed 1/3 (0.33), as per the MPI criteria (Alkire et al., 2022). Based on the multidimensional poverty index and its corresponding threshold values, farmers were categorized into two groups: multidimensionally poor and non-multidimensionally poor.

To determine the number of poverty dimensions for each sample, the values of the five dimensions were weighted and aggregated for each sample, taking into account the values of individual variables. This process yielded a multidimensional poverty score for each rural household, which was then used to calculate the multidimensional poverty index. The index ranged from 0 to 1, with higher values indicating higher levels of poverty. The multidimensionally poor households were further classified into vulnerable, general, and extreme multidimensional poverty categories based on the assigned weightings of each indicator. Among them, the cutoff for the Vulnerable Multidimensional Poverty Index (VMPI) was set at 33% ($0 \leq M < 1/3$), while households falling within the range of 33 to 66% ($1/3 \leq M < 2/3$) were considered General Multidimensional Poverty Index (GMPI). Finally, the threshold for Extreme Multidimensional Poverty Index (EMPI) was defined as 66% ($2/3 \leq M \leq 1$) (Xia et al., 2019).

Table 2 presents the outcomes of the one-dimensional poverty deprivation matrix, which was generated by applying the predetermined relative poverty line after conducting unidimensional poverty measurement for each dimension of rural households. The sample observation matrix was established based on the data collected through the questionnaire. The results of the measurement unveiled that the years of education dimension

Table 1 Dimensions, indicators, cutoffs, and weights of the MPI.

Dimension	Indicator (relative weight)	Deprived if...	Cutoffs
Health	Medical expenses (1/10)	Medical expenses incurred by a member of the family suffering from a serious illness or hospitalization	Qualitative indicator: 1 = poor; 0 = non-poor
	Health insurance (1/10)	A member of the family does not have rural health insurance	Qualitative indicator: 1 = poor; 0 = non-poor
Education	Years of education (1/5)	A member of the family who is 16 years of age or older and has less than 9 years of education.	9
Income	Per capita disposable income (1/5)	Household disposable income per capita is less than 40% of the national median disposable income per capita for rural residents in 2019	5755.6
Living standard	Electricity (1/25)	No electricity in the home	Qualitative indicator: 1 = poor; 0 = non-poor
	Cooking fuel (1/25)	The primary fuel for cooking is unclean fuel	Qualitative indicator: 1 = poor; 0 = non-poor
	Floor (1/25)	The structure is made of mud	Qualitative indicator: 1 = poor; 0 = non-poor
	Assets (1/25)	Households that do not own more than one of the following assets: battery car, car, television, Refrigerator, washing machine, telephone, air conditioner, computer, electric heater, or water heater	Qualitative indicator: 1 = poor; 0 = non-poor
	Per capita housing area (1/25)	Less than 12 square meters are seen as a sign of deprivation in terms of housing area per capital.	12
Labor force	Proportion of labor force to total household size (1/5)	The ratio of the labor force is less than 1/3	Qualitative indicator: 1 = poor; 0 = non-poor

Table 2 Smartphone usage and incidence of unidimensional poverty.

Dimension	Indicator (relative weight)	Poverty incidence			T-value
		Total (SD) N = 382	Smartphone usage (SD) N = 256	Smartphone non-usage (SD) N = 126	
	Multidimensional Poverty index (MPI)	0.428	0.245	0.518	
Health	Medical expenses (1/10)	0.768 (0.423)	0.675 (0.470)	0.813 (0.391)	2.842***
	Health insurance (1/10)	0.141 (0.349)	0.063 (0.245)	0.180 (0.385)	3.580***
Education	Years of education (1/5)	0.872 (0.335)	0.730 (0.446)	0.941 (0.235)	4.990***
Income	Per capita disposable income (1/5)	0.243 (0.430)	0.048 (0.214)	0.340 (0.475)	8.290***
Living standard	Electricity (1/25)	0.013 (0.114)	0.000 (0.000)	0.020 (0.139)	2.254**
	Cooking fuel (1/25)	0.034 (0.182)	0.008 (0.090)	0.047 (0.212)	2.523**
	Floor (1/25)	0.016 (0.125)	0.008 (0.090)	0.020 (0.139)	0.855
	Assets (1/25)	0.016 (0.125)	0.000 (0.000)	0.023 (0.152)	2.474**
	Per capita housing area (1/25)	0.013 (0.114)	0.000 (0.000)	0.020 (0.139)	2.254**
Labor force	Number of laborers (1/5)	0.644 (0.479)	0.318 (0.467)	0.805 (0.397)	10.051***

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

exhibited the highest poverty incidence, reaching an alarming rate of 87.2%. This finding indicated that a substantial majority of farm households had family members aged 16 or older with less than 9 years of education, emphasizing the educational challenges prevalent among rural communities.

Further analysis revealed interesting disparities in poverty incidence based on smartphone usage. Rural households that did not utilize smartphones demonstrated a considerably higher poverty incidence of 94.1% within the years of education dimension, whereas those who utilized smartphones had a comparatively lower poverty incidence of 73.0%. This discrepancy can be attributed to various factors. It is worth noting that the sample rural households selected for this study primarily consisted of older farmers who possessed extensive knowledge regarding household capital and agricultural practices. During their younger years, rural China experienced a low rate of educational penetration, which significantly limited the educational opportunities available to rural households and impeded their access to new technological products. Consequently, rural households that had access to Internet products such as

smartphones were likely to possess higher levels of education compared to farmers who did not have such access, leading to a relatively lower poverty incidence within the years of education dimension (Krell et al., 2021).

The second-highest poverty incidence was observed in the medical expenses dimension, where it reached 81.3% for rural households without smartphones. This indicates that nearly one-third of rural households had experienced the financial burden of medical treatments or had family members requiring hospitalization or suffering from serious diseases. The absence of smartphones among these households may contribute to their limited access to online health resources and preventive measures, potentially increasing their vulnerability to illnesses or hindering their ability to recognize and administer timely first aid when health issues arise (Jorm, 2012).

Importantly, the incidence of poverty related to the health insurance indicator within the health dimension was remarkably lower, standing at 14.1%. This demonstrates the significant role played by various state-provided health insurance programs for rural residents in alleviating the financial burden of medical

expenses and reducing the overall incidence of poverty. These programs have effectively mitigated the economic impact of healthcare costs on farmers (Song, 2014).

The labor force dimension exhibited the third-highest poverty incidence, with a rate of 64.4%. This indicates that over half of farm households had less than one-third of their household members actively participating in the labor force. The poverty incidence within the labor force dimension for farm households without access to smartphone usage was notably higher at 80.5%. This can be attributed to the presence of a higher proportion of elderly and vulnerable individuals within rural China, as well as imbalances in family structures. Additionally, the health issues faced by certain family members contribute to their reduced capacity for labor and place a heavy burden on the household (Basu and Meltzer, 2005).

The income component, with a poverty incidence of 24.3%, ranked fourth in terms of poverty prevalence. This signifies that approximately a quarter of farm households had per capita disposable income below the national median for rural inhabitants in 2019. When examining smartphone usage, it was found that 4.8% of farm households utilizing smartphones and 34% of those without smartphones were living in poverty. This highlights the transformative impact of widespread smartphone usage on rural households, as it has increased their employment opportunities and contributed to the reduction of poverty (Deng et al., 2019).

Lastly, the living standard dimension exhibited the lowest incidence of poverty. This suggests that rural households have experienced improvements in their access to electricity, drinking water, and housing conditions. The government's efforts in rural infrastructure development have yielded positive outcomes, contributing to the overall enhancement of living standards among rural communities.

Independent variable. In this study, the primary independent variable of interest revolved around the adoption of smartphones among rural households. The utilization of the internet through smartphones has emerged as a crucial factor influencing the production of goods and services within these communities. By expanding access to information and enhancing social capital, smartphone usage, particularly in underdeveloped regions, effectively addresses the prevalent issue of information fragmentation. Consequently, it stimulates employment opportunities, enhances productivity levels, and unlocks the untapped consumer potential within these areas. Smartphones are more prevalent due to their portability and user-friendly nature (Mayisela, 2013). Accordingly, the variable "1" was assigned to represent households utilizing smartphones, while "0" denoted those who did not employ smartphones in this study.

Mediating variable. This study incorporates social capital as a mediating variable, employing a measurement framework comprising four dimensions derived from existing literature: social networks, social trust, social participation, and social support (Ali-Hassan et al., 2015). Social capital, understood as a durable network of connections, serves as an informal form of capital that enables rural social networks to provide assistance and protection to households in the face of risks. The calculation of the entropy value for social capital is based on these four dimensions, culminating in the measurement of the overall social capital index.

Firstly, it is important to recognize that Chinese rural society is primarily characterized by a vernacular culture where acquaintances, family, and friends play pivotal roles as sources of information for rural households. Social networks serve as a means to bring individuals from diverse backgrounds together, facilitating communication, information sharing, and expanding the scope of knowledge transfer. This concept of "bridging social

capital" encompasses the ability to trade fresh knowledge or resources across various contexts (Ansari et al., 2012). Drawing upon Knoke's perspective, social networks are understood as structures consisting of numerous organizers, with participants connected through one or more relationships (Knoke and Yang, 2019). Such networks grant individuals access to diverse resources, including knowledge, morals, and financial support. In line with this, the study utilized the question "How many relatives in your family are village, township cadres, or other public officials?" as a proxy variable for social networks, building on Daley's research (Zhang et al., 2012).

Secondly, social trust is defined as an individual's expectations and beliefs regarding whether their own future behavior will influence the ethical standards of others, which subsequently impacts their own behavioral decisions. Social trust facilitates interpersonal relationships and serves as the foundation for sharing and cooperation. Trusting relationships enable individuals to anticipate each other's behavior. Social trust can be categorized into interpersonal trust and institutional trust (Luhmann, 1979). Trust in public institutions, such as the government, promotes cooperative behavior and facilitates the benefits of trust, such as cooperation and exchange. The level of trust within a society is positively associated with cooperation in achieving common goals (Brewer, 1999). To capture social trust, the study utilized the question "Do you trust the government?" as a proxy variable, with responses ranging from "very trusting" to "very distrustful," each assigned a value from 1 to 5.

Thirdly, social participation encompasses a rural household's concern, understanding, and active involvement in various aspects of social life. It represents a means to acquire resources through engagement in social activities, interaction with others, and support for integration within the community. For the purpose of this study, social participation was approximated using the question "Whether your family participates in organizations such as planting associations and cooperatives," assigning a value of 1 to households that engage in such activities and 0 to those that do not.

Lastly, within the interdependent and supportive vernacular society prevalent in rural China, all households coexist over extended periods. Social support, as a social resource derived from interpersonal ties, plays a role in the transmission and internalization of values, influencing value orientation, emotional attachment, and social identity. To capture social support, the research employed the question "How many people will come to help if the family holds weddings and funerals?" as a proxy variable. Overall, these four dimensions of social capital provide insights into the dynamics of rural households' social networks, trust, participation, and support, contributing to a comprehensive understanding of the mediating role of social capital in this study.

Control variables. The selection of control variables in this study is based on existing literature on multidimensional poverty, encompassing two levels: individual characteristics and household characteristics. By incorporating these variables, the study aims to mitigate potential biases stemming from other influential factors and account for the factors that significantly impact the multidimensional poverty status of households that have successfully overcome poverty. Examples of individual characteristics considered include gender, age, education level, and marital status of the household head. On the other hand, household characteristics encompass variables such as the total number of members, the number of individuals in the household labor force, and the total household income (log) (Xiao et al., 2022a, 2022b, 2022c). Table 2 displays each variable's precise definition.

Descriptive statistics. Table 3 presents the comprehensive definitions and descriptive statistics of the key variables selected for the

Table 3 Variable description.

Variable	Definition	Min	Max	Mean	SD
Dependent variable					
Vulnerable Multidimensional Poverty Index (VMPI)	Vulnerable multidimensional poverty rural households are those whose multidimensional poverty index is less than 0.33 ($0 \leq M < 1/3$); 1 = yes, 0 = no; binary variables	0	1	0.717	0.451
General Multidimensional Poverty Index (GMPI)	General multidimensional poverty rural households are those whose multidimensional poverty index is greater than or equal to 0.33 and less than 0.66 ($1/3 \leq M < 2/3$); 1 = yes, 0 = no; binary variables	0	1	0.576	0.495
Extreme Multidimensional Poverty Index (EMPI)	Extreme multidimensional poverty rural households are those whose multidimensional poverty index is greater than or equal to 0.66 ($2/3 \leq M \leq 1$); 1 = yes, 0 = no; binary variables	0	1	0.141	0.349
Independent variable					
Smartphone usage	Whether use smartphones; 1 = yes, 0 = no; binary variables	0	1	0.330	0.470
Mediating variable					
Total social capital index	Social capital after entropy value	0	0.903	0.225	0.235
Social networks	How many relatives in your family are village, township cadres, or other public officials; continuous variable	0	2	0.235	0.553
Social trust	Do you believe in the government; 1 = very trusting, 2 = trusting, 3 = general, 4 = distrustful, 5 = very distrustful	1	5	3.298	1.199
Social participation	Whether your family participates in organizations such as planting associations and cooperatives; 1 = yes, 0 = no; binary variables	0	1	0.397	0.490
Social support	How many people will come to help if the family holds a red and white wedding; continuous variable	0	90	14.505	14.008
Individual characteristics					
Gender	Gender of rural household; 1 = male, 0 = female; binary variables	0	1	0.821	0.383
Age	Age of rural household; continuous variable	18	92	59.185	14.941
Education	Years of education in rural household; continuous variable	0	16	4.229	3.386
Marriage	Marital Status; 1 = unmarried, 2 = first marriage, 3 = remarried, 4 = divorced, 5 = widowed	1	5	2.583	1.438
Household characteristics					
Number of families	Continuous variable	1	7	2.850	1.577
Number of the labor force	Continuous variable	0	5	0.926	1.057
Income	Logarithm	0	11.51	8.831	3.352
Number of samples	382				

model. Examining the multidimensional poverty status of farmers, the analysis revealed that 71.7% of rural households fell within the category of *VMPI*, while 57.6% were classified as *GMPI*, and 14.1% were categorized as *EMPI*. These findings showed that the number of rural households experiencing multidimensional poverty as the criteria for poverty determination become more stringent.

Smartphone usage statistics indicated that 33.0% of rural households utilized smartphones. Notably, the interview sample primarily consisted of vulnerable populations such as the elderly and children left behind in rural areas, which explained the relatively low levels of smartphone usage. Even though households have successfully overcome poverty, persistent poverty and a decline in the labor force have resulted in a long-term impoverished situation (McCulloch and Calandrino, 2003).

Regarding social capital, the overall social capital index for rural households was found to be 0.225. Furthermore, the mean value for social networks was 0.235, indicating a limited scope of social connections. Social trust exhibited a mean value of 3.298, indicating a moderate level of trust within the community. Social participation scored a mean value of 0.397, suggesting a relatively low engagement in social activities. The mean value for social support was 14.55, indicating a modest level of support available to rural households. These findings collectively suggest that rural households generally possess low levels of overall social capital, limited social networks, restricted social participation, and inadequate social support.

Analyzing the personal characteristics of rural households, it was observed that 82.1% of the respondents were men. This trend can be attributed to the survey's focus on household heads and farmers who possess decision-making authority and

comprehensive knowledge about their household situation. The average age of the sample rural households was 59.185 years, indicating an aging population within rural areas. Moreover, the average years of formal schooling was 4.229, indicating a prevalent lack of formal education among the majority of farmers. Additionally, the mean marital status score of 2.583 suggests that most rural households were married.

Considering the household characteristics of rural households, the average family size was 2.850, indicating relatively small household units. The average number of laborers per household was 0.926, which highlights a notable disparity compared to other types of households, suggesting a lower proportion of laborers in farm households. Finally, the logarithm of the average total household income was 8.831, representing the overall income level of rural households.

The results of the independent sample T-test for the primary variables selected in the model are presented in Table 4. To examine the multidimensional poverty status of rural households, independent sample T-tests were employed to create two distinct sample groups based on their smartphone usage. The mean values of the vulnerable *VMPI* (0.950), *GMPI* (0.750), and *EMPI* (0.210) for rural households without smartphones were found to be significantly higher (at the 1% level) than the mean values of the *VMPI* (0.240), *GMPI* (0.230), and *EMPI* (0.210) for rural households with smartphone usage. These findings provide preliminary evidence suggesting that rural households using smartphones were less susceptible to experiencing multidimensional poverty.

Regarding the social capital of rural households, it was observed that rural households without smartphones exhibited

Table 4 Mean comparison between smartphone usage group and smartphone non-usage group.

Variable	Smartphone usage group (n = 126)		Smartphone Non-usage group (n = 256)		T-value
	Mean	SD	Mean	SD	
Dependent variable					
VMPI	0.240	0.428	0.950	0.212	17.730***
GMPI	0.230	0.423	0.750	0.436	10.982***
EMPI	0.010	0.089	0.210	0.406	7.489***
Mediating variable					
Total Social Capital Index	0.428	0.266	0.125	0.133	-12.097***
Social networks	0.651	0.772	0.031	0.195	-8.861***
Social trust	3.786	1.129	3.059	1.162	-5.806***
Social participation	0.698	0.461	0.250	0.434	-9.115***
Social support	15.056	14.527	14.234	13.766	-0.538
Individual characteristics					
Gender	0.802	0.400	0.832	0.375	0.730
Age	56.500	15.200	60.508	14.662	2.481**
Education	5.270	3.785	3.717	3.052	-4.009***
Marriage	2.532	1.390	2.609	1.465	0.495
Household characteristics					
Number of families	3.262	1.415	2.652	1.614	-3.775
Number of the labor force	1.516	1.018	0.641	0.956	-8.236***
Income	10.142	1.718	8.186	3.752	-6.984***

Note: ** and *** indicate significance at the 5%, and 1% statistical levels, respectively; values in parentheses are regression standard errors.

lower mean values for their total social capital index (0.125), social networks (0.031), social trust (3.059), and social participation (0.250) compared to farmers who used smartphones. Conversely, rural households with smartphone usage demonstrated higher mean values for their total social capital index (0.428), social networks (0.651), social trust (3.786), and social participation (0.698), all of which were statistically significant at the 1% level. These results suggest that smartphone usage among farmers is associated with higher levels of social capital across various dimensions.

When examining the personal characteristics of rural households, a notable finding emerges: the mean age of rural households using smartphones (56.600) was significantly lower compared to households not using smartphones (60.508), with statistical significance observed at the 5% level. This suggests that younger individuals are more inclined to utilize the Internet through smartphones, while older individuals may be less inclined to adopt this technology.

Furthermore, the analysis reveals a significant disparity in educational attainment between the two groups. Rural households using smartphones exhibited a higher mean level of education (5.270) in comparison to households not using smartphones (3.717), demonstrating a substantial difference that was statistically significant at the 1% level. This indicates that individuals with a higher level of education are more likely to engage with smartphone technology and access the Internet.

In terms of household characteristics, it is noteworthy that rural households using smartphones displayed a higher mean value for the labor force (1.516) in contrast to rural households not using smartphones (0.641). This difference was statistically significant at the 1% level, suggesting that smartphone usage may contribute to greater labor force engagement within rural households.

Additionally, the mean income value of rural households utilizing smartphones (10.142) was significantly higher compared to rural households that did not adopt smartphones (8.186), with statistical significance observed at the 1% level. This finding suggests that smartphone usage may be associated with a higher level of household income among rural communities.

Methods

The A-F multidimensional poverty methodology. In this study, Alkire and Foster’s “dual cut-off approach” (also known as the A-F method) is used to quantify multidimensional poverty. Due to the poverty identification step’s usage of “double cut-off” dimensions and deprivation cut-off values, the A-F multidimensional poverty index also incorporates poverty identification and summing. This component is sometimes referred to as the “double cut-off approach”. The calculation of an individual’s poverty status within each dimension involves several steps. Firstly, the poverty line is determined for each dimension. Then, a threshold for dimensional poverty is established, and individuals are classified as poor if their measurement of dimensional poverty exceeds this threshold. The process encompasses three key steps: identification of unidimensional and multidimensional poverty, measurement, and deconstruction.

Identification of one-dimensional poverty: To elaborate further, let us define the variables used in this process. We denote “n” as the total number of individuals and “d” as the number of indicators under analysis. Consequently, we obtain an n*d dimensional sample observation matrix, denoted as X = [x_{ij}], which represents the achievement of individual i in indicator j. Specifically, each element x_{ij} of the matrix X belongs to the real number set R, indicating the quantitative measurement of the individual i’s performance in indicator j. To clarify, i takes values from 1 to n, representing the range of individuals included in the study, while j takes values from 1 to d, signifying the various indicators examined:

$$X = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1d} \\ x_{21} & x_{22} & \dots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nd} \end{pmatrix} \tag{1}$$

To determine deprivation in each indicator, a cutoff value (z_j) is set, and if an individual’s well-being value falls below this cutoff, they are considered deprived in that dimension (as shown in Table 1).

The deprivation cutoffs are collected in a row vector Z, while a matrix G = [g_{ij}] is created to represent individuals’ deprivation status across the indicators. The element g_{ij} in the matrix indicates whether an individual i is deprived (1) or not deprived (0) in indicator j:

$$G = \begin{pmatrix} g_{11} & g_{12} & \dots & g_{1d} \\ g_{21} & g_{22} & \dots & g_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \dots & g_{nd} \end{pmatrix} \tag{2}$$

If x_{ij} < z_j, then g_{ij} = 1, indicating that the individual is deprived in the indicator; if x_{ij} ≥ z_j, then i_{ij} = 0, indicating that individual i is not deprived in the indicator, that is:

$$g_{ij} = \begin{cases} 1, & x_{ij} < z_j \\ 0, & x_{ij} \geq z_j \end{cases} \tag{3}$$

Identification of multidimensional poverty: This study employs the dimension equal weight method, where the vector of weights (w_j) is utilized to denote the equal importance assigned to each indicator (j), then $\sum_{j=1}^d w_j = 1$. By applying this approach, the multiple dimensions of poverty are aggregated through summation to derive the multidimensional poverty index (MPI) for each individual (i):

$$MP_i = \sum_{j=1}^d w_j * g_{ij} \tag{4}$$

This study builds upon the work of Pasha as a theoretical framework. We assign a value of $k=1/3$, representing the threshold for poverty determination. The poverty cutoff is implemented through the identification method, denoted as p_i , which categorizes individual i as experiencing multidimensional poverty if their deprivation score exceeds or equals k , i.e., $MP_i \geq k$. Conversely, if the deprivation score falls below k , it indicates a state of non-multidimensional poverty:

$$P_i = \begin{cases} 1 & MP_i \geq k \\ 0 & MP_i < k \end{cases} \tag{5}$$

Next, the number of multidimensional poor households is identified, and the multidimensional deprivation matrix Q :

$$P = \begin{pmatrix} p_{11}(1) & p_{12}(2) & \dots & p_{1d}(d) \\ p_{21}(1) & p_{22}(2) & \dots & p_{2d}(d) \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1}(1) & p_{n2}(2) & \dots & p_{nd}(d) \end{pmatrix} \tag{6}$$

Multi-dimensional poverty index calculation: We perform three main calculations to analyze multidimensional poverty. Firstly, we determine the multidimensional headcount ratio (H), which measures the proportion of individuals identified as experiencing multidimensional poverty among the total sample.

Secondly, we calculate the average deprivation among the poor by summing the deprivation scores of all individuals in poverty and dividing them by the total number of poor individuals. This gives us the intensity of multidimensional poverty (A), indicating the extent of deprivation across different dimensions for the poor.

Finally, we combine the headcount ratio (H) and the intensity (A) to obtain the multidimensional poverty index (M). The index is calculated by multiplying these two values ($M = H \times A$), providing a comprehensive measure of multidimensional poverty. The number of multi-dimensional poor people is represented by q , and the formula is as follows:

$$H = \frac{\sum_{i=1}^n P_i}{n} \tag{7}$$

$$A = \frac{1}{q} \sum_{i=1}^q P_i \tag{8}$$

$$M = HA \tag{9}$$

Dimensional decomposition: Furthermore, we conduct a decomposition analysis of the multidimensional poverty index by individual indicators. The contribution of each dimension to the overall multidimensional relative poverty index is denoted as M_j , while q_j represents the total count of individuals experiencing multidimensional poverty and deprivation in that specific dimension. The contribution rate of each indicator to the

multidimensional poverty index is:

$$I_j = \frac{q_j / N^{w_j}}{M} \tag{10}$$

Multivariate ordered logistic model. This study aims to investigate the influence of smartphone usage on the multidimensional poverty of rural households. To achieve this, an ordinary least squares (OLS) linear regression model was employed to estimate the standardized multidimensional poverty index as the dependent variable. The study proceeded in four sequential steps to comprehensively analyze the relationships involved.

The first step involved constructing a model to assess the direct impact of smartphone usage on rural households' multidimensional poverty (Model 11). Subsequently, in the second step, a separate model was developed to examine the influence of smartphone usage on rural households' social capital (Model 12). Building upon the insights obtained from the previous two steps, the third step incorporated the information to construct a model that explores the contribution of social capital to the relationship between smartphone usage and multidimensional poverty (Model 13). To test the mediating effect, a Bootstrap self-sampling method was employed, repeating the analysis 1000 times. The setup model was as follows:

$$Y_{i,t} = c + \alpha_1 X_{i,t} + \sum Control_{i,t} + \varepsilon_{i,t} \tag{11}$$

$$M_{i,t} = c + \alpha_2 X_{i,t} + \sum Control_{i,t} + \varepsilon_{i,t} \tag{12}$$

$$Y_{i,t} = c + \alpha_3 X_{i,t} + \beta_1 M_{i,t} + \sum Control_{i,t} + \varepsilon_{i,t} \tag{13}$$

Among the variables utilized in the analysis, $X_{i,t}$ denotes the level of smartphone usage in rural households, $M_{i,t}$ represents the social capital level of these households, and $Y_{i,t}$ signifies their multidimensional poverty status. Furthermore, the constant term is denoted by c , the coefficient vector group is represented by α_i , and the random error term is indicated by $\varepsilon_{i,t}$. To ensure the reliability of the findings, the model's robustness was assessed. In the econometric analysis, robust standard errors were employed to mitigate the potential impact of heteroscedasticity on the model outcomes. The above econometric models were all implemented by Stata 16.0.

Results

Multidimensional poverty index analysis

Multidimensional poverty index measurement. In this study, a comprehensive measurement system for multidimensional poverty was constructed by selecting 10 indicators across 5 dimensions. Threshold values were established to determine the poverty status of each indicator, enabling the calculation of the level of deprivation when the threshold was surpassed. By assessing the deprivation levels within each dimension for each sampled household, the cumulative count of deprived dimensions was computed. Additionally, a critical threshold for the number of deprived dimensions was set, and individuals were classified as experiencing multidimensional poverty when the number of deprived dimensions exceeded this threshold.

To investigate the extent of multidimensional poverty among the rural households in the sample, three key measures were calculated: the incidence of poverty (H), the level of deprivation (A), and the multidimensional poverty index (M). The multidimensional poverty index (M) is obtained by multiplying H and A , providing a comprehensive assessment of both the breadth and depth of poverty. H represents the proportion of rural households experiencing multidimensional poverty in relation to the total number of rural households, reflecting the breadth of multidimensional poverty occurrence. On the other hand, A represents

Table 5 Multidimensional poverty measurement results.

K	Incidence of multidimensional poverty (H)			Degree of multidimensional poverty deprivation (A)			Multidimensional Poverty Index (M)		
	Total	Smartphone non-usage	Smartphone usage	Total	Smartphone non-usage	Smartphone usage	Total	Smartphone non-usage	Smartphone usage
1/10	0.982	1.000	0.944	0.455	0.522	0.311	0.446	0.522	0.293
2/10	0.950	0.996	0.857	0.466	0.523	0.332	0.443	0.521	0.285
3/10	0.874	0.980	0.659	0.490	0.528	0.372	0.428	0.518	0.245
4/10	0.704	0.934	0.238	0.535	0.539	0.499	0.376	0.503	0.119
5/10	0.555	0.730	0.198	0.570	0.576	0.519	0.316	0.421	0.103
6/10	0.212	0.305	0.024	0.677	0.679	0.633	0.144	0.207	0.015
7/10	0.037	0.055	—	0.761	0.761	—	0.028	0.042	—
8/10	0.008	0.012	—	0.800	0.800	—	0.006	0.009	—
9/10	—	—	—	—	—	—	—	—	—
10/10	—	—	—	—	—	—	—	—	—

the average number of deprived dimensions among poor rural households in relation to the total number of dimensions, indicating the depth of multidimensional poverty occurrence.

Table 5 presents the results of the estimations of multidimensional deprivation for rural households, considering different threshold values (K) for multidimensional relative poverty. As the threshold value increased, the criteria for identifying economic and living aspects of poverty became more rigorous and stringent, leading to a rapid reduction in the number of impoverished households. The analysis revealed that the majority of households exhibited deficits in only a few dimensions, while a minority of households were free from poverty across all five areas, namely education, health, living standards, income, and labor force.

When comparing rural households with and without smartphones, the findings demonstrated significant differences in multidimensional poverty indicators. The incidence of H, A, and M were all notably higher for households without smartphones, indicating a greater vulnerability to multidimensional relative poverty.

Moreover, M and H consistently declined as k increased, while A rose. For instance, when employing threshold values of K = 1/10 and K = 9/10, M for the entire sample was calculated as 0.446 and 0, respectively. M exhibited a decreasing trend with increasing threshold values, following an inverted U-shaped pattern, initially rising and then declining.

Interestingly, the incidence of poverty among rural households using smartphones reached 0 when K reached 0.7, indicating that no households experienced poverty in all five dimensions. Similarly, for rural households without smartphones, the incidence of poverty reached 0 when K reached 0.9, signifying the absence of poverty across all five dimensions in the entire sample. These results demonstrated that rural households using smartphones tended to overcome multidimensional poverty at a faster rate compared to those without smartphones.

Dimensional contribution of multidimensional poverty index. The findings of the supplementary investigation conducted in this study regarding the contributions of each dimension to multidimensional poverty among households out of poverty are

Table 6 Dimensional contribution rate of multidimensional poverty index unit: %.

Dimension	Total	Smartphone Non-usage	Smartphone Usage
Health	0.204	0.191	0.259
Education	0.378	0.357	0.466
Income	0.113	0.131	0.032
Living standard	0.009	0.010	0.003
Labor force	0.297	0.311	0.240

presented in Table 6. It was observed that the labor force and education dimensions had the most significant contributions when k was set at 0.33, accounting for 67.5% of multidimensional poverty in the sample of rural households.

In terms of comparing rural households using smartphones with those not using smartphones, the poverty contribution rates differ across various dimensions. Rural households using smartphones demonstrate higher poverty contribution rates in the health and education dimensions, indicating a greater prevalence of poverty in these areas compared to farmers who do not use smartphones. Conversely, rural households using smartphones exhibit lower poverty contribution rates in the income, living conditions, and labor force dimensions. This finding suggests that rural households utilizing smartphones are more likely to belong to a better-educated group, engage in intellectual activities, and rely on educational opportunities to alleviate poverty (Engle and Black, 2008). However, it should be noted that excessive use of smartphones or other electronic devices may have adverse effects on health, exposing individuals to additional health concerns (Kim et al., 2016).

Impact of smartphone usage on multidimensional poverty. The impact of smartphone usage on multidimensional poverty among rural households is presented in Table 7. Regression analysis

Table 7 Total sample linear estimation results for the poverty reduction effect of smartphone usage.

Variable	VMPI		GMPI		EMPI	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Smartphone Usage	-0.715*** (0.040)	-0.576*** (0.050)	-0.516*** (0.046)	-0.526*** (0.058)	-0.120*** (0.027)	-0.050* (0.026)
Gender	—	0.067* (0.034)	—	0.117** (0.054)	—	-0.050 (0.043)
Age	—	0.002** (0.001)	—	0.003* (0.002)	—	-0.001 (0.001)
Education	—	-0.017*** (0.005)	—	-0.005 (0.007)	—	-0.012*** (0.004)
Marriage	—	0.014 (0.010)	—	0.034** (0.016)	—	-0.020 (0.012)
Number of families	—	0.057*** (0.012)	—	0.005 (0.019)	—	0.052*** (0.014)
Number of labor force	—	-0.127*** (0.023)	—	-0.039 (0.031)	—	-0.088*** (0.020)
Income	—	-0.013*** (0.004)	—	-0.033*** (0.009)	—	-0.047*** (0.007)
N	382	382	382	382	382	382
F	315.06	155.48	123.38	25.01	56.03	14.24
R-squared	0.557***	0.637***	0.241***	0.315***	0.072***	0.302***

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively; values in parentheses are regression standard errors.

results from Models 1 and 2 examined the relationship using the explanatory variable *VMPI*, while Models 3 and 4 analyzed the results using the explanatory variable *GMPI*. Furthermore, Models 5 and 6 showcased the outcomes using the explanatory variable *EMPI*. Initially, without considering the influence of control variables, Models 1, 3, and 5 indicated that smartphone usage led to a substantial reduction in the *VMPI* by 71.5%, the *GMPI* by 51.6%, and the *EMPI* by 12%, respectively. These reductions were all statistically significant at the 1% level. In contrast, when accounting for the effects of the control variables, Models 2, 4, and 6 demonstrated that smartphone usage still contributed to a decrease in poverty levels, albeit to a lesser extent. The *VMPI* decreased by 57.6%, the *GMPI* by 52.6%, and the *EMPI* by 5%. These findings supported hypothesis 1, suggesting that smartphone usage could effectively reduce the incidence of multidimensional poverty. However, the significance of smartphone usage diminished as the definition of multidimensional poverty became more refined.

According to a study conducted by Ma et al. (2018), the utilization of smartphones plays a significant role in expanding the horizons and information access for rural households. It enhances their knowledge and provides them with opportunities for employment in sectors such as e-commerce, logistics, and services. This increased connectivity and access to resources are the primary drivers behind the reduction of multidimensional poverty among rural households. However, it is worth noting that the poverty-alleviating effect of smartphones gradually diminishes as the criteria for identifying poverty become more stringent. In the case of general multidimensional poverty and extreme multidimensional poverty, rural households face deprivation across multiple dimensions and suffer from limited development capacity and sustainable livelihood capital. As the study by Rizqulloh and Firmansyah (2021) suggests, the Internet, despite being one of the tools for poverty alleviation, may not fully penetrate all aspects of life.

The level of multidimensional poverty experienced by rural households is influenced by various personal and household characteristics. In terms of personal characteristics, the gender of rural households was found to exacerbate their multidimensional poverty, with a statistically significant increase of 6.7% for *VMPI* and 11.7% for *GMPI*, at the 10 and 5% levels, respectively. Furthermore, the age of the farmer was found to contribute to an increase of 0.2% in *VMPI* and 0.3% in *GMPI*, with statistical significance at the 5% and 10% levels, respectively. This could be attributed to the limited prospects for development and reduced employment opportunities as rural households age. In Model 2 using *VMPI* as the explanatory variable, the gender (6.70%) and

age (0.20%) of rural families worsened the *VMPI* of rural households, which were statistically significant at 5% and 10%, respectively. The *VMPI* of rural households, which was statistically significant at the 1% level, decreased by the educational attainment of rural households (1.70%). In terms of the household characteristics of rural households, total household size (5.70%) and total labor force (12.70%) enhanced and reduced the degree of *VMPI* of rural households at 1% level of significance, respectively; household income of rural households (1.30%) alleviated the degree of *VMPI* at 1% level of significance. In Model 4 with *GMPI* as the explanatory variable, gender (11.70%), age (0.30%), and marital status (3.40%) of rural households increased the degree of *GMPI* of rural households, which were significant at 10%, 5%, and 5% statistical levels, respectively. At the 1% level of significance, the household income of rural households (3.30%) reduced the *GMPI* of rural households. In Model 6, where *EMPI* was used as the explanatory variable, the number of years of education in rural households exhibited a significant reduction of 1.20% in the degree of *EMPI* among farm households, at the 1% level of significance. Concerning the household characteristics of rural households, the total household size contributed to a significant increase of 5.20% in the *EMPI* among farmers, while the total labor force showed a significant reduction of 8.80%. These effects were both significant at the 1% level of significance. Additionally, the household income of rural households displayed a significant decrease of 4.70% in *EMPI*, at the 1% level of significance.

As individuals age, their work capacity tends to decline, resulting in diminished development prospects and an increase in poverty rates (Massey, 1996). In the study area, men exhibit a higher likelihood than women in reducing multidimensional poverty as they possess a better understanding of the household situation and have more decision-making power within the household. Furthermore, higher levels of education among farmers contribute to an expanded knowledge base and a lower overall incidence of multidimensional poverty (Ayuya et al., 2015). A larger labor force within a household can generate additional income and resources, aiding rural households in escaping relative poverty (Buvinić and Gupta, 1997). However, it is important to note that a larger overall household size also brings about increased expenses and obligations, such as healthcare and education, which can make farm households more susceptible to poverty (Ruben, 2001). Nonetheless, a larger labor force can effectively contribute to increased income and resources for rural households, facilitating their escape from relative poverty (Buvinić and Gupta, 1997). Notably, income plays a critical role in reducing *VMPI*, *GMPI*, and *EMPI*. Its significance is particularly pronounced for rural households experiencing *EMPI*, as

Table 8 Results of mediating effects of smartphone usage on poverty reduction.

Variable	Social Capital		VMPI		GMPI		EMPI	
	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Smartphone usage	0.304*** (0.025)	0.328*** (0.025)	-0.842*** (0.033)	-0.689*** (0.046)	-0.687*** (0.041)	-0.694*** (0.056)	-0.155*** (0.027)	0.005 (0.028)
Social capital	—	—	0.418*** (0.088)	0.342*** (0.078)	0.562*** (0.104)	0.510*** (0.102)	-0.144** (0.059)	-0.167*** (0.057)
Control variable	—	Yes	—	Yes	—	Yes	—	Yes
N	382	382	382	382	382	382	382	382
F	146.92	24.82	324.86	160.65	140.50	39.91	27.67	12.70
R-squared	0.369***	0.403***	0.587***	0.657***	0.286***	0.350***	0.078***	0.310***

Note: ** and *** indicate significance at the 5%, and 1% statistical levels, respectively; values in parentheses are regression standard errors.

they require support in both production and livelihood aspects. Income can swiftly alleviate short-term poverty and is indispensable for enhancing sustainability. Thus, focusing on improving educational attainment and increasing the number of family workers can be an effective strategy (Kaygusuz, 2011).

The intermediary role of social capital. The results of the linear estimation, exploring social capital as a mediating variable, are presented in Table 8. Models 7 and 8 investigated the relationship between smartphone usage and rural households’ social capital in the absence and presence of control variables, respectively. The findings indicated a positive association between smartphone usage and social capital among rural households when other variables were not taken into account, suggesting that smartphone usage enhanced the social capital of rural households. In Model 8, which incorporated control variables based on Model 7, the positive relationship between smartphone usage and rural households’ social capital remained.

Additionally, Models 9 and 10 examined the association between smartphone usage, social capital, and rural households’ VMPI, both without and with control variables. Model 9 demonstrated that in the absence of other variables, smartphone usage had the potential to reduce rural households’ VMPI by enhancing their social capital. Model 10, which included control variables based on Model 9, confirmed that smartphone usage could still mitigate rural households’ VMPI by boosting their social capital. These findings suggested that social capital acted as a partial mediator in the relationship between smartphone usage and rural households’ VMPI.

Models 11 and 12 were employed to investigate the associations between smartphone usage, social capital, and GMPI among rural households. Model 11 examined these relationships without the inclusion of control variables, while Model 12 incorporated control variables. The findings from Model 11 revealed that smartphone usage contributed to a reduction in GMPI among rural households by fostering the development of their social capital. This indicates that smartphone usage plays a significant role in alleviating GMPI when other variables are not taken into account. In Model 12, which incorporated control variables based on Model 11, the relationship between smartphone usage, social capital, and GMPI persisted. Smartphone usage continued to exhibit a significant reduction in GMPI among rural households by enhancing their social capital, thus suggesting that social capital partially mediates the relationship between smartphone usage and GMPI.

Models 13 and 14 were employed to investigate the associations between smartphone usage, social capital, and EMPI among rural households. In Model 13, no control variables were included, while in Model 14, control variables were incorporated. In the absence of

control variables (Model 13), the findings revealed that smartphone usage positively contributed to the enhancement of social capital among rural households experiencing EMPI. Model 14 accounted for the control variables identified in Model 13. The results indicated that smartphone usage did not have a significant impact on EMPI in rural households. However, social capital emerged as a fully mediating factor at the 1% significance level. This outcome could be attributed to the numerous deficiencies and low levels of development and education prevalent in rural households facing EMPI.

Social capital within rural households encompasses diverse elements such as social networks, social trust, social participation, and social support, derived from both individuals and family members. It serves as a valuable tool for comprehending the interplay between poverty and well-being within the context of a “relational” society in China. Through the utilization of social capital, individuals can access scarce resources, attain tangible benefits, or supplement productive assets, thus aiding rural households in alleviating poverty (Kaygusuz, 2011). Importantly, the acquisition of social capital is not solely facilitated by smartphones. It contributes to elevating the educational levels of rural households, augmenting their productive resources, and promoting sustainability. This is particularly noteworthy for impoverished rural households facing multifaceted challenges in various aspects of life (Barbier, 2010).

These findings lend support to hypothesis 2, which posits that smartphone usage mitigates multidimensional poverty in rural households by altering the mediating role of social capital. Specifically, social capital acts as a complete mediator between smartphone usage and EMPI while partially mediating the alleviating effects of smartphone usage on VMPI and GMPI.

Robustness test. Smartphone usage was found to significantly reduce VMPI, GMPI, and EMPI among rural households when as the above-mentioned explanatory variables. Computer usage served as a proxy variable for robustness testing, which helped to further support the validity of the results. Table 9 displays the results of the regression. Models 15 and 16 passed the 1% significance level test, proving that computer usage reduced rural households’ VMPI and GMPI, respectively. Model 18 passed the 1% significance level test, proving that rural households’ social capital is raised with computer usage. Models 19 and 20 both passed the 1% significance level test, indicating that by boosting rural households’ social capital, computer usage reduced VMPI and GMPI. The preceding conclusion was still reached when the explanatory factors were measured via computer access to the Internet, which ensured the validity of the investigation presented in this work.

Mediating effect test. The confidence intervals for the direct and indirect effects were calculated using the parametric percentile

Table 9 Estimated results of computer usage on multidimensional poverty.

Variable	VMPI Model 15	GMPI Model 16	EMPI Model 17	Social capital Model 18	VMPI Model 19	GMPI Model 20	EMPI Model 21
Computer usage	−0.532*** (0.052)	−0.491*** (0.059)	−0.041 (0.025)	0.335*** (0.027)	−0.622*** (0.052)	−0.643*** (0.060)	0.021 (0.028)
Social capital	—	—	—	—	0.271*** (0.082)	0.454*** (0.104)	−0.184*** (0.059)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	382	382	382	382	382	382	382
Wald chi ² (9)	130.10	24.13	14.13	23.63	128.14	34.89	12.62
Pseudo R ²	0.592***	0.287***	0.302***	0.409***	0.604***	0.315***	0.311***

Note: *** indicate significance at the 1% statistical level; values in parentheses are regression standard errors.

residual bootstrap method and the bias-corrected parametric percentile residual bootstrap method, respectively, with the number of replicate samples set at 1000 and the 95% confidence intervals calculated. This was done to further test the mediating effect of social capital. The outcomes of this analysis are presented in Table 10. The findings indicated that social capital indeed played a mediating role in the relationship between smartphone usage and both *VMPI* and *GMPI*. This was evidenced by the confidence intervals for the direct and indirect effects, obtained through the two aforementioned methods, which excluded zero.

In contrast, when examining the relationship between smartphone usage and *EMPI*, the confidence intervals for the direct effects of social capital included zero for both methods tested. However, the confidence intervals for the indirect effects did not include zero. These results suggested that social capital had a fully mediated effect on the relationship between smartphone usage and extreme multidimensional poverty.

Based on the calculations, it was determined that social capital accounted for 91.67% of the variance variation in the relationship between smartphone usage and *EMPI*, 20.84% of the variance variation in the relationship between smartphone usage and *GMPI*, and 14.09% of the variance variation in the relationship between smartphone usage and *VMPI*. These figures highlight the substantial contribution of social capital in explaining and influencing these complex relationships.

Discussion

The concerted efforts to eradicate poverty greatly benefited from the widespread popularization of the Internet in rural areas. The extensive adoption of smartphone usage played a significant role in fostering the growth of the digital economy in rural regions, creating employment and entrepreneurship opportunities, increasing farmers' incomes, and effectively combining poverty eradication endeavors to ensure sustainability. In light of these developments, this study delved into the examination of the mechanisms underlying the impact of smartphone usage on the multidimensional poverty experienced by rural households, utilizing social capital as a mediating variable.

The investigation reveals a relationship between smartphone usage and multidimensional poverty reduction. The findings indicate that the adoption of smartphones leads to a significant reduction in poverty levels, as evidenced by the decrease in the Extreme Multidimensional Poverty Index by 5%, the General Multidimensional Poverty Index by 52.6%, and the Vulnerable Multidimensional Poverty Index by 57.6%. However, the intriguing aspect lies in the observation that the magnitude of this reduction diminishes as the identification of multidimensional poverty becomes more comprehensive. This diminishing impact can be attributed to multiple factors. Firstly, as the dimensions of poverty under consideration expand, the complexity of addressing each dimension also

increases. Smartphones, while facilitating access to critical resources and information, may have a more prominent effect on certain dimensions than others. This leads to a gradual decline in the overall poverty reduction impact as the analysis broadens its scope, with the diminishing returns stemming from the varying nature and reach of smartphone benefits across diverse dimensions, this is consistent with Wang et al. (2023).

Social capital, characterized by improved access to information, resources, and opportunities facilitated by smartphones, plays a pivotal role in reducing poverty by promoting economic activities, enhancing knowledge dissemination, and enabling collective action. The profound mediating effect of social capital on extreme multidimensional poverty is particularly noteworthy, constituting 91.67% of the mediating effects. Smartphone usage facilitates the accumulation of social capital by providing avenues for information exchange, market access, and collective action. The fully mediating role in extreme multidimensional poverty reduction underscores the transformative power of smartphones in connecting marginalized communities with opportunities that transcend geographic and resource limitations. In cases of vulnerable and general multidimensional poverty, while social capital's mediating effects are partial, they still signify a substantial contribution to poverty alleviation (Deng et al., 2019; Foley and Edwards, 1999; Knoke and Yang, 2019).

This research made notable contributions in three key areas. Firstly, when measuring multidimensional poverty, careful consideration had to be given to the selection of dimensions. In addition to the three dimensions commonly utilized in the MPI framework—education, health, and living conditions—this article incorporated income and labor force indicators as two separate dimensions for measuring both single and multidimensional poverty.

Furthermore, this study employed a comprehensive evaluation of rural households' social capital, encompassing four key dimensions: social support, social participation, social trust, and social networks. By measuring various facets of social capital, the study provided more accurate and representative statistics.

Finally, to ensure reliable estimation results, the robustness of the findings was examined by using computer usage as a proxy for smartphone usage. To assess mediating effects, the study employed the parametric percentile residual bootstrap method and the bias-corrected parametric percentile residual bootstrap method, generating 1000 self-samples to calculate the confidence intervals for direct and indirect effects.

Although this paper provides a comprehensive analysis of the relationship between smartphone usage and multidimensional poverty reduction, along with the mediating role of social capital, there are still certain gaps that warrant further investigation.

To begin with, it is important to acknowledge that over 80% of the land area in Jiangxi Province was previously afflicted by poverty,

Table 10 Parameter bootstrap mediating effect test: social capital as a mediating variable.

Variable	Parametric percentile residual bootstrap method		Bias-corrected parametric percentile residual bootstrap method		Mediation effect amount (%)
	Direct effect	Indirect effect	Direct effect	Indirect effect	
Social capital					
VMPI	-0.689*** (-0.771, -0.601)	0.113*** (0.061, 0.165)	-0.689*** (-0.766, -0.593)	0.113*** (0.059, 0.163)	14.09%
GMPI	-0.694*** (-0.797, -0.576)	0.167*** (0.103, 0.241)	-0.694*** (-0.799, -0.579)	0.167*** (0.101, 0.240)	20.84%
EMPI	0.005 (-0.048, 0.059)	-0.055*** (-0.094, -0.023)	0.005 (-0.052, 0.057)	-0.055*** (-0.090, -0.019)	91.67%

Note: *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

and rural households continue to exhibit multiple indicators of poverty, despite the paper’s incorporation of five dimensions—education, health, living standards, income, and labor force—to measure poverty. In Jiangxi Province, however, factors such as industrial development and transportation accessibility significantly influence the production and functioning of rural households, making it challenging to accurately identify and alleviate poverty due to the complex and diverse nature of poverty characteristics. Conducting additional field research would enable future studies to incorporate these indicators into the measurement framework, facilitating a more comprehensive analysis of multidimensional poverty in Jiangxi Province.

Secondly, the management of relative poverty necessitates a universalistic approach that accounts for differentiation and multidimensionality. Poverty reduction strategies should be tailored to address the specific challenges faced by economically unviable household units. While the paper endeavors to explain the factors contributing to the lack of viability among rural households from the perspective of social capital, it is crucial to give due consideration to the psychological dimension that hinders the development of impoverished individuals. Attention should be directed towards addressing the mental well-being and empowerment of the poor.

Lastly, the research group in this study comprises rural households residing in poverty-eradication areas of Jiangxi Province, encompassing individuals of diverse age groups and cultural backgrounds. However, there is a dearth of rigorous research on multidimensional poverty in specific population groups within China. Adolescents and women, as highlighted in the Human Development Report 2019, are particularly vulnerable to poverty. Therefore, it is essential to emphasize research focused on these special populations, as well as the elderly, in the pursuit of eradicating multidimensional poverty.

In conclusion, while this paper makes significant contributions to the understanding of smartphone usage, social capital, and multidimensional poverty reduction, further investigations are required to address the identified gaps. By incorporating additional indicators, considering the psychological dimension of poverty, and conducting targeted research on specific vulnerable populations, future studies can deepen our understanding of multidimensional poverty and inform more effective poverty alleviation strategies.

Conclusions

This paper constructed a comprehensive theoretical framework for analyzing the reduction of multidimensional poverty through smartphone usage, adopting a social capital perspective. The study utilized research data from 382 rural households in five counties and districts of Jiangxi Province as the sample. The objective was to explore the impact and mechanisms of smartphone usage in poverty reduction while considering the multidimensional nature of poverty. The findings of this study were as follows:

- (1) Analysis of the total sample revealed that the incidence of multidimensional poverty among rural households was 42.80%. However, for households using smartphones, the incidence dropped to 24.5%, whereas for households not using smartphones, it rose to 51.80%.
- (2) By dividing the sample farmers into smartphone users and non-smartphone users, an independent sample *t*-test was conducted, and multidimensional poverty was classified into three categories: Vulnerable Multidimensional Poverty Index ($0 < M < 1/3$), General Multidimensional Poverty Index ($1/3 \leq M < 2/3$), and Extreme Multidimensional Poverty Index ($2/3 \leq M < 1$), based on the MPI. The findings indicated that rural households not using smartphones exhibited higher mean values in the Vulnerable Multidimensional Poverty Index (0.950), General

Multidimensional Poverty Index (0.750), and Extreme Multidimensional Poverty Index (0.210) compared to smartphone-using farmers, who had lower mean values in the Vulnerable Multidimensional Poverty Index (0.240), General Multidimensional Poverty Index (0.230), and Extreme Multidimensional Poverty Index (0.010).

- (3) Significant variations in poverty incidence were observed across different dimensions, highlighting the persistently challenging situation of unidimensional poverty. Evaluating unidimensional poverty in each dimension, the incidence of poverty for the entire sample ranked from highest to lowest across the ten dimensions as follows: years of education (87.20%), medical expenses (76.80%), labor force (64.40%), per capita disposable income (24.30%), health insurance (14.10%), cooking fuel (3.40%), floor and assets (1.60%), electricity (1.30%), and per capita housing area (1.30%).
- (4) Education, labor force, and health emerged as the key contributors to multidimensional poverty, with varying degrees of impact from each component on the poverty index. The study analyzed multidimensional poverty using ten indicators across five dimensions and examined the contribution rate of each indicator to rural households' overall multidimensional poverty (with a poverty threshold value, $K = 0.33$). The results revealed that the three crucial areas for long-term poverty alleviation in Jiangxi Province were health (37.80%), labor force (29.70%), and education (20.40%).
- (5) To measure multidimensional poverty, the paper established multiple threshold values and calculated the multidimensional poverty index using ten indicators across five dimensions. The findings indicated that as deprivation categories became more stringent, the multidimensional poverty index decreased. However, the rate of decline diminished, displaying an inverted U-shaped pattern characterized by an initial increase followed by a decline.
- (6) The adoption of smartphones significantly reduced the level of multidimensional poverty among rural households. However, as the identification of multidimensional poverty became more comprehensive, the impact of poverty reduction diminished. Specifically, smartphones lowered the Vulnerable Multidimensional Poverty Index by 57.6%, the General Multidimensional Poverty Index by 52.6%, and the Extreme Multidimensional Poverty Index by 5%.
- (7) The primary mechanism through which smartphone usage reduced multidimensional poverty was by enhancing rural households' social capital and long-term sustainability. Social capital played a fully mediating role in alleviating Extreme Multidimensional Poverty Index through smartphone usage, accounting for 91.67% of the mediating effects. In the case of vulnerable multidimensional poverty and general multidimensional poverty, social capital partially mediated the effects.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Received: 18 July 2023; Accepted: 9 January 2024;

Published online: 20 January 2024

Notes

1 Source: Ministry of Agriculture and Rural Affairs http://www.moa.gov.cn/nygb/2020/202002/202004/t20200414_6341529.htm

2 The MPI is a three-dimensional measure of poverty, comprising a total of ten indicators: health: nutritional status, child mortality; education: child enrollment, and educational attainment; and standard of living: drinking water, electricity, fuel for daily use, indoor space, sanitation and consumer durables. See <https://baike.so.com/doc/25727498-26857836.html>.

3 Source from China Rural Revitalization Comprehensive Survey Report 2021

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Acknowledgements

This research was funded by the National Natural Science Foundation of China project, grant numbers 42161053 and 42101310; the Scientific Research Development Fund Project of Zhejiang A&F University, grant number 2022FR014.

Author contributions

All authors contributed to the study's conception and design. Conceptualization, all authors; formal analysis, XL, HX, and LL; investigation, all authors; writing—original draft preparation, HX, XL, and LL; writing—review and editing, FH, LH, and GX; visualization, FH and GX. All authors commented on previous versions of the manuscript. XL and HX contributed equally to this work. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

This study is not related to human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1057/s41599-024-02645-x>.

Correspondence and requests for materials should be addressed to Longjunjiang Huang.

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