frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 01 August 2025
DOI 10.3389/fsufs.2025.1595575

Check for updates

OPEN ACCESS

EDITED BY
Siphe Zantsi,
Agricultural Research Council of South Africa (ARC-SA), South Africa

REVIEWED BY
Mashford Zenda,
University of Johannesburg, South Africa
Faiz Faiz,
Swinburne University of Technology, Australia

*CORRESPONDENCE
Lizhi Tang
✉ tanglizhi@xmu.edu.cn

RECEIVED 18 March 2025
ACCEPTED 03 July 2025
PUBLISHED 01 August 2025

CITATION
Tang Y and Tang L (2025) Digital technology adoption and farm household income in ethnic minority areas: evidence from Xinjiang, China. *Front. Sustain. Food Syst.* 9:1595575. doi: 10.3389/fsufs.2025.1595575

Digital technology adoption and farm household income in ethnic minority areas: evidence from Xinjiang, China

Yan Tang and Lizhi Tang*

Department of Statistics and Data Science, School of Economics, Xiamen University, Xiamen, Fujian, China

Introduction: Promoting rural income growth and equity remains a critical concern for academia and policymakers. With the rapid development of the digital economy, digital technologies have emerged as key drivers of rural revitalization. However, digital inclusiveness in ethnic minority areas has not received sufficient attention. This topic is not only related to inclusive growth objectives but also directly impacts the progress and benefits of comprehensive rural revitalization.

Methods: Using micro-survey data from Xinjiang in 2023, this study constructs a digital technology adoption index characterized by digital production, digital information processing, and digital marketing. An endogenous switching regression model is employed to address potential selection bias arising from unobservable factors, examining the impact of digital technology adoption on rural household income in ethnic regions and its underlying mechanisms. A quantile treatment effect model is used to capture heterogeneous impacts on income distribution.

Results: Digital technology adoption and its sub-dimensions significantly enhance rural household incomes. The core mechanism lies in strengthening agricultural production and operational capabilities and driving a shift in household livelihood strategies from traditional agriculture-dominated to diversified models. Specifically, digital adoption reduces reliance on traditional labor inputs in agricultural production, boosting agricultural incomes while increasing the likelihood of non-farm employment, thereby promoting income diversification. The income effect of digital adoption varies across income quantiles, with stronger impacts on low-income households than on middle-to-high-income households, contributing to narrowed rural income inequality.

Discussion: To our knowledge, this is the first study focusing on the digitalization process in minority ethnic areas of China. It contributes to understanding the actual progress of digitalization in remote ethnic rural areas, providing theoretical support and practical insights for achieving inclusive growth goals in multi-ethnic regions and formulating differentiated agricultural economic policies.

KEYWORDS

digital technology adoption, ethnic minority area, farm household income, income distribution, endogenous switching regression, quantile treatment effects

1 Introduction

Ethnic minority areas[1] are key and challenging in China's agricultural and rural modernization. Promoting rural revitalization in these areas is crucial for the comprehensive revitalization of rural areas, regional coordinated development, and common prosperity. Income growth has always been the central task of China's initiatives related to agriculture, rural areas and farmers, and it has also been a challenge in ethnic regions. Remarkably, these efforts have yielded significant results. By the end of 2020, 98.99 million rural impoverished individuals had successfully lifted themselves out of absolute poverty by current standards. During the period from 2016 to 2020, the cumulative number of impoverished people in ethnic minority groups and regions decreased by 15.6 million.[2] Taking Xinjiang as an example, in 2020, all 3.0649 million rural impoverished people were lifted out of poverty, marking a historic resolution of absolute poverty.[3] Figure 1 shows the growth trend of per capita disposable income among rural residents in China's five ethnic autonomous regions. Although the absolute value remains below the national average, the growth rate has consistently outpaced the national level since 2015, demonstrating strong development momentum.

Meanwhile, the digital economy is thriving, and the widespread application of digital technologies has provided new solutions for advancing agricultural and rural modernization (Maina et al., 2024). The Digital China initiative was officially proposed at the Second World Internet Conference in 2015, after which the construction of digital villages rapidly became a strategic direction for rural revitalization and a key component of Digital China. At the end of 2022, the number of rural internet users in China had reached 308 million, with an internet penetration rate of 61.9% in rural areas, representing an increase of 113 million users and a 33.5% improvement, respectively, compared with 2015.[4] Big data, artificial intelligence, the Internet of Things, and other digital technologies have been gradually integrated into various fields of agriculture and rural areas, reshaping the inherent structure and form of rural society, and driving agricultural transformation and upgrading, the sustainable progress of rural areas, and the comprehensive development of farmers. Especially in remote areas with relatively weak information foundations, major network coverage projects such as "network poverty alleviation" and "broadband connectivity for every village" have effectively alleviated the long-standing information gap, exerting a profound impact on the production methods and lifestyle of local farmers. Ethnic minority regions in China are predominantly distributed in the economically less-developed western and border areas. Constrained by factors such as remote geographic locations, lagging industrial development, and insufficient endogenous drivers, these regions have long been focal points of poverty alleviation efforts in China. Households in these areas have limited access to new technological information, and the widespread adoption of digital technology can alleviate their information and skills constraints, potentially leading to income growth (Zheng et al., 2021; Zhu et al., 2021). So, is the excellent performance of income growth among rural residents in ethnic minority areas closely related to the digital transformation of agriculture and rural areas? On the one hand, with vast territories and abundant natural, folk, and historical cultural resources yet to be fully explored, ethnic minority rural areas have the potential to achieve leapfrog development and narrow the gap with developed regions through the application of digital technology. On the other hand, the uneven dissemination of digital technologies may result in the uneven distribution of digital dividends (World Bank, 2016). This imbalance can be attributed to the disparities in innate endowments and acquired abilities among individuals in embracing new technologies, potentially resulting in ethnic minority rural farmers becoming a vulnerable group in the digital era. In a market economy, digital resources tend to flow to regions and groups with higher returns on capital. This tendency may deviate from inclusive growth objectives and exacerbate inequality in opportunities faced by vulnerable groups. Therefore, investigating whether and how the adoption of digital technology plays a role in improving the income of rural households in ethnic minority areas is undoubtedly a research topic of significant importance.

The digital transformation of agriculture and rural areas has garnered significant attention in policymaking across various countries (World Bank, 2017, 2019; Rijswijk et al., 2021). Existing literature generally emphasizes the importance of digitization in driving income growth for rural residents. Muto and Yamano (2009) demonstrated that augmented mobile phone coverage enhances market participation by farmers in remote regions and those engaged in the production of perishable agricultural commodities. Aker (2010) illustrated that mobile phone penetration markedly diminishes price dispersion in Niger's grain market, primarily due to decreased search costs, enabling traders to swiftly access price information from multiple markets. Hubler and Hartje (2016) found that smartphone ownership has a significant positive impact on household income based on survey data from rural households in Southeast Asia. In the context of China, Zhou et al. (2020) utilized Ordinary Least Squares (OLS) regression, drawing on data from the 2016 China Family Panel Studies (CFPS), to reveal that internet usage significantly promotes income growth among rural residents. Xie et al. (2023) further validated, using Probit models on CFPS data, that internet access significantly decreases the likelihood of farmers falling into relative poverty. Building on the income effect, Hou et al. (2019), based on field surveys of northern Chinese households, employed the propensity score matching (PSM) method to determine that computer usage by farmers led to increased leased farmland areas, reduced labor intensity, higher probabilities of direct

1 China is home to 56 ethnic groups, with the Han being the largest ethnic group, while the other 55 groups are referred to as ethnic minorities. Ethnic minority areas refer to the areas where ethnic minorities live together.

2 Data source: Chinese government website, Poverty Alleviation: China's Experience and Contribution. https://www.gov.cn/zhengce/2021-04/06/content_5597952.htm.

3 Data source: Xinjiang Uygur Autonomous Region People's Government Website, Statistical Bulletin on National Economic and Social Development of Xinjiang Uygur Autonomous Region 2020. https://www.xinjiang.gov.cn/xinjiang/tjgb/202106/5037ac528c58479dbaabddce9050a284.shtml.

4 Data source: China Internet Network Information Center (CNNIC), 51st Statistical Report on Internet Development in China. https://www3.cnnic.cn/n4/2023/0302/c199-10755.html.

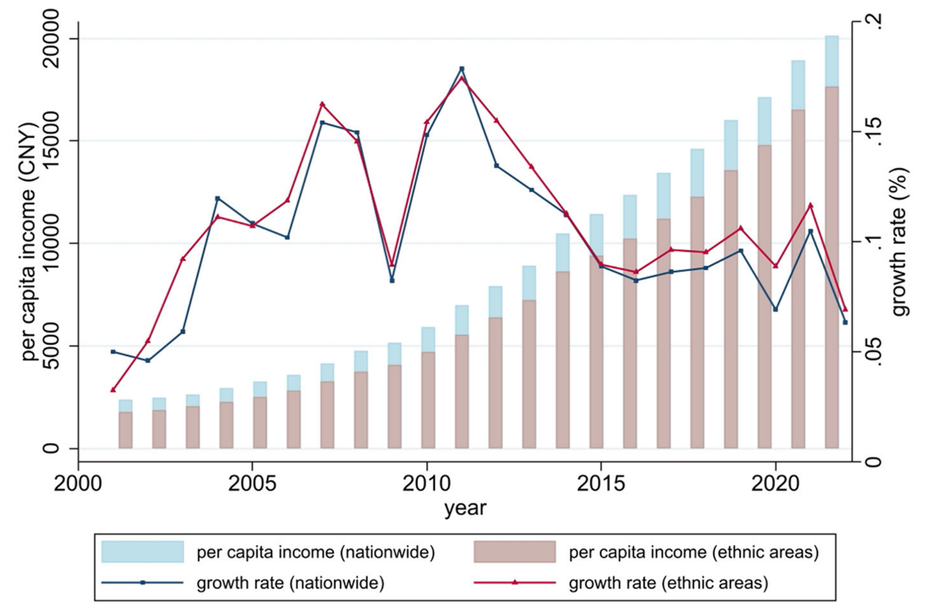

FIGURE 1
Comparison of per capita disposable income in rural minority areas with the national average from 2002 to 2022 [data source: National Bureau of Statistics of the People's Republic of China, China Statistical Yearbook (2003–2023). Prior to 2013, the statistical indicator for rural residents' income was per capita net income, which was later adjusted to per capita disposable income].

agricultural product sales, and stimulated consumption growth. Hong and Chang (2020), focusing on forestry households in Fujian Province, showed that internet-using households earned ∼28% higher incomes than non-users, with enhanced access to technical information serving as a key mechanism, while also significantly improving life satisfaction. Nevertheless, there are studies pointing out the limitations of the income-enhancing effects of digital technologies. For example, Tadesse and Bahiigwa (2015) indicated that in rural Ethiopia, despite the rapid expansion of mobile phone coverage, only a small number of farmers use mobile phones as a channel to access market information. Aker and Ksoll (2016) further highlighted that the impact of mobile phone technology varies across regions, gender, mobile phone ownership, and market access, and is not consistent everywhere, without a significant overall improvement in household economic welfare. Zhou and Deng (2023) further revealed that rural internet penetration essentially represents a process of creative destruction, with destructive effects currently dominating while creative roles are yet to be fully realized.

Prior research provides valuable insights into understanding the relationship between digital technology adoption and rural residents' income. However, there is room for further improvement in the following areas. First, the existing literature often defines digital technology adoption in general terms as the adoption of networked devices, such as mobile phones and computers (Aker and Ksoll, 2016; Hou et al., 2019) or the access to the internet (Zhou et al., 2020; Hong and Chang, 2020; Zhou and Deng, 2023). While such definitions are somewhat applicable in describing the widespread trend of digital technology diffusion, they appear overly broad and lack rationality when exploring the relationship between the adoption of digital technology and farmers' production economic activities. This is because farmers may utilize network devices and the internet for activities unrelated to their economic production endeavors. Thus, it is imperative to provide a more precise and specific definition of digital technology adoption. Second, previous studies have often failed to fully consider the issue of self-selection bias resulting from both observable and unobservable factors in the adoption of digital technology. While some studies have utilized PSM methods to address selection bias stemming from observable variables (Hou et al., 2019; Hong and Chang, 2020; Zhou and Deng, 2023), this approach does not address the selection bias introduced by unobservable variables, thereby compromising the validity of estimation results. Third, the discussion on digital technology and income inequality has predominantly concentrated on inter-regional (Qiu et al., 2021) or urban–rural income disparities (Xia et al., 2024), with a paucity of studies examining the influence of digitization on intra-rural income disparities. Furthermore, the extant literature has yet to integrate the income-enhancing consequences of digital technology adoption and discrepancies in the initial endowments of farm households into a unified research framework. Fourth, while previous studies have concentrated on the influence of internet usage on household income in economically developed regions or nationally representative areas, they have not addressed whether and to what extent digital technology adoption influences the income situation of households in minority ethnic regions.

Digital inclusiveness in rural and ethnic minority regions represents an understudied and pressing issue, particularly in the western border regions of China. Digital inclusiveness not only concerns the accessibility of information communication technologies but also emphasizes compatibility, pluralism, participation, and sharing (Weerakkody et al., 2012). Here, compatibility embodies pluralistic values, enabling different groups to integrate into the digital society; pluralism focuses on diverse actors and their interest demands, aiming to eliminate digital exclusion arising from social identity, ethnic, and class differences; participation is dedicated to creating opportunities for all social groups to engage in various aspects of the digital society; and sharing ensures that all citizens, especially digital vulnerable groups, can equitably enjoy the dividends of digital technology development. Taken together, these four dimensions underscore the importance of tailoring digitalization efforts to safeguard the interests and capacity to benefit of vulnerable and marginalized groups. Ethnic minority areas in China, particularly in the western border regions (such as Xinjiang), face unique challenges such as sparse population, complex ethnic structure, limited resource increments, and complex governance environments. In recent years, border rural areas in China have achieved varying degrees of development through various support policies. However, it cannot be ignored that there still exists a certain gap in development between rural areas in border ethnic regions and those in inland areas. This study not only responds to the concerns of digital inclusiveness theory for vulnerable groups but also considers the impacts brought by ethnic heterogeneity, enhancing the research's sensitivity at the cultural and demographic levels. The research conclusions can not only provide theoretical and practical insights for multi-ethnic regions to achieve inclusive growth but also further test the universality of digital inclusion theory, deepen the understanding of the heterogeneous impacts of digital technology diffusion, and provide a scientific basis for formulating more inclusive regional development policies.

Based on this, this study uses field survey data from Xinjiang Uygur Autonomous Region in China in 2023 to empirically analyze the impact and mechanisms of digital technology adoption on the income of ethnic minority households from a micro perspective. Moreover, the study examines the potential impact of digital technology on income disparity within rural areas. Compared to previous studies, the contribution of this study may be as follows. First, this study designs a series of questionnaire questions directly related to the use of digital technology and constructs digital technology adoption indicators characterized by digital production, digital information processing and digital marketing, rather than merely using the ownership of computers, smart phones, or access to the internet as indicators of digital technology adoption. Second, this study has a dual research objective. In addition to examining the income effects of household adoption of digital technology, it also answers the important question of whether diverse income groups can equally benefit from the digital dividend, thereby extending research on rural residents' income in the context of digitization. Third, in terms of research methodology, this study adopts the endogenous switching regression (ESR) model and the quantile treatment effect (QTE) model, which integrates the study of income-enhancing effects and the differences in the initial endowments of farm households into the same research framework for investigation. Compared with other models, the ESR model can better solve the endogeneity issues resulting from omitted variables and unobservable factors, while the QTE model allows for examining the heterogeneity of the impact of digital technology adoption on the income effect of farm households with different initial endowments, providing a scientific basis for evaluating the income-enhancing effects of technology and informing policy formulation. Fourthy, to the best of our knowledge, this is the first article to focus on digitization in ethnic minority regions in China. Exploring the causal relationship between the adoption of digital technologies by ethnic minority farm households and their household income can help to understand the actual progress of the digitization process in China's remote ethnic minority rural areas and inform the formulation of relevant inclusive growth targets and agricultural economic policies.

The remainder of this study is organized as follows. Section 2 builds a theoretical framework for examining the impact of digital technology adoption on household income, based on theoretical analysis and literature review. Additionally, research hypotheses are proposed. Section 3 describes the data sources, empirical strategies employed, and variable definitions. Section 4 analyzes the estimated results of the impact of digital technology adoption on income growth. Section 5 presents the empirical findings and analysis regarding the impact of digital technology adoption on income distribution. Finally, Section 6 concludes the study by summarizing the key findings.

2 Theoretical analysis and research hypotheses

2.1 Digital technology adoption and income growth

There are numerous determinants of household income growth, and within the context of the digital economy era, the spread and application of digital technology in the agricultural and rural sectors has become the key factor in reshaping the production and lifestyle of rural residents. Currently, scholars have extensively explored the relationship between internet usage and farmer income. For instance, Chang and Just (2009), through an analysis of survey data from farming households in Taiwan, China, revealed a significant positive impact of internet access on enhancing household income. Gao et al. (2018) utilized panel data at the provincial level from 2000 to 2013 in China, and they found that the increased penetration rate of computers in rural areas can contribute to higher household income. The increase in farm income and non-farm income is the main source of income growth of farm households, among which the growth of non-farm income has become the focus of scholars' research in recent years. Khanal et al. (2015) estimated data from a survey of U.S. farming households using the nearest neighbor matching method, revealing that small farms with internet access perform better in terms of total household income and non-agricultural income. Zhou et al. (2020) examined the promotion effect of internet usage on farmer income growth from the perspectives of entrepreneurship and non-agricultural employment using OLS regression analysis.

However, the popularization of the internet in rural areas is only one of the many aspects of building digital villages, and the application scenarios of digital technology in agricultural and rural areas go far beyond that. Based on a micro perspective of rural residents' production and operations, this study defines the

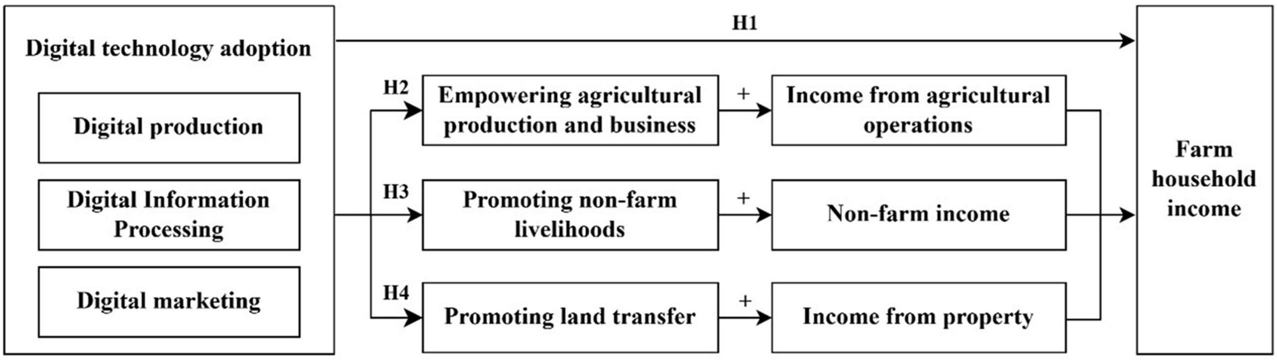

FIGURE 2
Mechanisms underlying the impact of digital technology adoption on farm household income.

adoption of digital technology by households as the utilization of digital technology or tools to advance the digitization transformation in key aspects such as production, decision-making, and marketing within their operations. Specifically, this study elaborates on the characteristics of households' adoption of digital technology from three dimensions: digital production, digital information processing, and digital marketing. In terms of digital production, this study focuses on the application of digital agriculture, where farmers' involvement in digital production primarily involves utilizing advanced digital technologies such as smart agricultural machinery, the Internet of Things, big data, and so on, to optimize production processes, improve production efficiency, and promote the realization of precision agriculture and intelligent management (Sparrow and Howard, 2021). In the dimension of digital information processing, households leverage information and communication technologies to effectively overcome barriers of information asymmetry, swiftly and cost-effectively acquire necessary information for production and operations, thereby improving the quality of decision-making and management behavior (Shen et al., 2022). In terms of digital marketing, the participation of households mainly includes utilizing digital channels such as e-commerce platforms (e.g., Taobao, JD, Meituan) and social media (e.g., WeChat, TikTok, Little Red Book) to expand the sales network of agricultural products and handicrafts, or promote rural tourism (Liu et al., 2021). Accordingly, we propose the following hypothesis:

> Hypothesis 1: Digital technology adoption and its various dimensions have a promoting effect on farm household income growth.

While some scholars have confirmed the impact of internet usage on farmers' income growth, previous studies often fail to specify the specific types of technology when exploring the relationship between internet usage and farmers' income, resulting in an insufficient explanation of the mechanisms through which the adoption of digital technology enhances income. With regards to income composition, the impact mechanism of adopting digital technology on farmers' agricultural and non-agricultural income may differ. This study innovatively combines the perspectives of household livelihood strategy selection and optimal allocation of production factors, systematically analyzing the impact mechanism of adopting digital technology on household income growth from three aspects: agricultural production and operations, non-farm livelihood strategies, and land transfer decisions (Figure 2).

2.2 Empowering agricultural production and operation

The digital revolution has brought about a transformation in the agricultural industry (Benyam et al., 2021; Shen et al., 2022), with its impact being felt across the entire agricultural value chain, primarily encompassing the following aspects.

First, farmers have achieved the intelligent and precision management of the agricultural production process by employing digital technologies, such as the Internet of Things and artificial intelligence, as well as smart agricultural machinery like crop protection drones, satellite navigation, and intelligent cotton-picking machines, significantly enhancing resource utilization efficiency and agricultural productivity (Mondejar et al., 2021). For example, in Manas County, Changji Prefecture, farmers have utilized IoT technology to connect soil sensors with irrigation systems, enabling precise drip irrigation of water and fertilizer. This not only reduces agricultural input costs and labor expenses but also enhances the accuracy and efficiency of irrigation, playing a role in lowering costs and increasing efficiency.

Second, the agricultural sector confronts various uncertainties, such as natural risks and market fluctuations, all of which can potentially lead to diminished agricultural returns. The application of digital technologies can reduce farmers' information search costs, alleviate information asymmetry in agricultural production and marketing (Li et al., 2021), and assist farmers in accessing timely and accurate market information (Wolfert et al., 2017). Therefore, digital technology adoption helps farmers optimize production and management decisions, thus improving agricultural business returns.

Third, the application of digital technologies has enhanced the marketing methods of agricultural products. Through online sales models such as B2B and B2C, it is possible to reduce losses in the agricultural product distribution process, broaden sales channels

(Deller et al., 2019), and thereby mitigate the negative impact of geographic limitations on minority areas. Based on the analysis above, we propose the following hypothesis:

Hypothesis 2: Digital technology adoption and its various dimensions contribute to increasing agricultural business income, thus promoting growth in farmer incomes.

2.3 Promoting transfer of non-agricultural livelihoods

The application of digital technologies has provided new pathways for livelihood strategy transformation for farmers, prompting them to shift from traditional agriculture-dominant livelihood models to diversified or non-agricultural livelihood strategies. Throughout this process, the impact of digital technology adoption on farmers' livelihood strategies is primarily manifested in the following three aspects:

In the digital production dimension, digital technology is not only a key factor in enhancing productivity but also plays a pivotal role in facilitating the continuous updating of individual skills and knowledge (Li et al., 2023). By operating digital devices, farmers can continuously learn and acquire new skills in practice, thereby improving production efficiency and labor capacity. Furthermore, the application of digital technologies in agricultural production also reduces labor intensity, freeing up surplus labor. This surplus labor can transition from the agricultural sector to non-agricultural activities, such as wage labor or entrepreneurial endeavors, thereby expanding the channels for income sources for farmers and increasing their non-agricultural income.

In the dimension of digital information processing, the adoption of digital technologies helps facilitate employment matching and identification of entrepreneurship opportunities (Tsai, 2001). The utilization of digital technologies enables farmers to more effectively access employment information, alleviating issues of labor market information asymmetry, reducing search costs for both labor demanders and suppliers, and increasing the likelihood of farmers engaging in non-agricultural work (Goldfarb and Tucker, 2019), thereby enhancing farmers' wage income. Moreover, the use of digital technologies provides farmers with channels to acquire professional and business knowledge. Convenient access to information can assist entrepreneurs in identifying entrepreneurial opportunities (Bowen and Morris, 2019) and increasing their likelihood of entrepreneurial success, consequently boosting their business income (Zhang et al., 2018).

In the digital marketing dimension, the adoption of digital technologies provides a practical foundation and potential for farmers to engage in diversified entrepreneurial activities (Zhou et al., 2020). Digital technologies enhance the flexibility, interconnectedness, and openness of entrepreneurial endeavors, offering a new catalyst for promoting farmer entrepreneurship and income enhancement. Compared to traditional rural entrepreneurship, leveraging digital marketing channels, such as e-commerce platforms and social media, enables farmers to promptly respond to market dynamics, transcend geographical limitations, broaden their outreach, and engage in real-time interactions with customers through diverse digital platforms, effectively attracting clientele. The preceding analysis leads to the following hypothesis:

Hypothesis 3: Digital technology adoption and its various dimensions can facilitate the transition to non-farm livelihoods and contribute to increasing non-farm income, thus promoting growth in farmer incomes.

2.4 Promoting land transfer

Land transfer is a crucial decision for farmers to optimize the allocation of household production factors. Existing research generally suggests that digital technologies, represented by the internet, can alleviate information asymmetry in the land transfer market, reducing transaction costs associated with land transfer (Wu et al., 2023), thereby enhancing the likelihood of farmer participation in land transfer (Tchamyou et al., 2019). The application of digital technologies in agriculture will strengthen internal specialization and professionalization within the agricultural sector, driving the differentiation of rural labor (Min et al., 2020). In this context, the optimal allocation of land resources becomes an inevitable trend, making the land transfer market more active. For farmers, on one hand, the adoption of digital technologies can enhance agricultural operational income and increase the attractiveness of land cultivation (Zhang et al., 2018); on the other hand, it may also increase the opportunity cost of engaging in cultivation by promoting non-agricultural employment and entrepreneurship, increasing the willingness to transfer land, and thus increasing the property income. Whether farmers choose to transfer land depends on the comparison between the sum of the opportunity cost of cultivating their own land and land rent, and agricultural operational income. Assuming that the former is greater than the latter, the hypothesis would be as follows:

Hypothesis 4: Digital technology adoption and its various dimensions can promote land transfer and contribute to increasing property income, thus promoting growth in farmer incomes.

3 Empirical strategy and data

3.1 Estimation strategies

3.1.1 Endogenous switching regression model

This study focuses on the impact of digital technology adoption on farm household income, establishing the following basic equation:

$$Y_i = \alpha D_i + \beta X_i + \varepsilon_i \tag{1}$$

where Y_i represents the income of the farm household; D_i is a dummy variable, with $D_i = 1$ indicating the adoption of digital technology, and $D_i = 0$ indicating non-adoption; X_i represents a vector of control variables potentially related to farm household income, including household characteristics, individual characteristics of the household head, regional features. ε_i is an error term.

Farmers may self-select the adoption of digital technologies based on their intrinsic characteristics (e.g., ability) and expected returns. In addition, certain unobservable factors could simultaneously impact both households' decisions on the adoption of digital technologies and household income. In such cases, utilizing the OLS method might lead to estimation bias due to disregarding selection biases and underlying endogeneity issues. Although PSM method is widely utilized to address issues of self-selection bias (Hou et al., 2019; Nikam et al., 2022; Ma et al., 2024), it can only rectify selection bias associated with observable factors, failing to control for the influence of unobservable factors (Liu et al., 2021). Some scholars resort to the instrumental variable (IV) method to tackle endogeneity problems arising from omitted variables (Hou et al., 2019; Zhou et al., 2020; Hong and Chang, 2020), yet this approach may yield significant fitting biases due to heterogeneity among households and sample selection biases.

Drawing from the approach of Lassalas et al. (2024), this study employs the ESR model proposed by Lokshin and Sajaia (2004). This model addresses sample selection bias stemming from both observable and unobservable factors (Kumar et al., 2018) and fits income determination equations for households that have and have not adopted digital technologies, along with their counterfactual equations, thereby compensating for the shortcomings of the aforementioned research methods. The fundamental concept of ESR involves a two-stage estimation approach: the first stage encompasses the regression of the selection equation using Probit regression, estimating whether households adopt digital technologies and the factors influencing this decision. The second stage entails estimating the outcome equation and conducting income equation estimations for the adopter and non-adopter separately to validate income discrepancies among households in different contexts. Furthermore, an effective method for estimating the ESR model is the full-information maximum-likelihood (FIML) estimation (Di Falco et al., 2011), which simultaneously estimates one selection and two outcome equations, yielding consistent standard errors.

The behavioral decision equation for households is constructed as follows:

$$D_i^* = \gamma Z_i + \mu_i \text{ with } D_i = \begin{cases} 1 \text{ if } D_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

where D_i^* represents the latent variable of the dummy variable D_i with $D_i = 1$ when $D_i^* > 0$, and $D_i = 0$ when $D_i^* \leq 0$. Z_i is a vector of variables that influence households' decisions to adopt digital technologies, while μ_i denotes the random error term. It is noteworthy that the explanatory variables in Z_i can overlap with X_i. However, to address selection bias, Z_i should include at least one instrumental variable that exerts a direct influence on the decision of a farmer to adopt a digital technology, without directly affecting their income. The outcome equations for households that adopt and do not adopt digital technologies can be respectively described as follows:

Regime 1 (digital technology adopter):

$$Y_{i1} = \beta_1 X_{i1} + \varepsilon_{i1} \ \ if \ \ D_i = 1 \tag{3a}$$

Regime 2 (digital technology non-adopter):

$$Y_{i0} = \beta_0 X_{i0} + \varepsilon_{i0} \ \ if \ \ D_i = 0 \tag{3b}$$

where Y_{i1} and Y_{i0} represent household incomes for adopters and non-adopters of digital technologies, respectively. X_i denotes the vector of exogenous variables that potentially affect the outcomes. ε_{i1} and ε_{i0} are the random disturbances associated with the outcome variables.

According to Di Falco et al. (2011), the expected incomes of adopters and non-adopters of digital technologies in both the real and counterfactual scenarios can be calculated as follows:

$$E(Y_{i1}|D_i = 1) = \beta_1 X_{i1} + \sigma_{1\mu}\lambda_{i1} \tag{4a}$$

$$E(Y_{i0}|D_i = 1) = \beta_0 X_{i1} + \sigma_{0\mu}\lambda_{i1} \tag{4b}$$

$$E(Y_{i0}|D_i = 0) = \beta_0 X_{i0} + \sigma_{0\mu}\lambda_{i0} \tag{4c}$$

$$E(Y_{i1}|D_i = 0) = \beta_1 X_{i0} + \sigma_{1\mu}\lambda_{i0} \tag{4d}$$

where $\sigma_{1\mu}$ and $\sigma_{0\mu}$ represent the covariance between μ_i and ε_{i1}, ε_{i0}, respectively. λ_{i1} and λ_{i0} are the inverse Mills ratios for the adoption and non-adoption of digital technologies. According to Lokshin and Sajaia (2004), if $\sigma_{1\mu}$ and $\sigma_{0\mu}$ are statistically significantly different from zero, the null hypothesis of no selection bias can be rejected. Following Di Falco et al. (2011), the average treatment effect on the treated (ATT) for digital technology adoption can be derived as the difference between Equation 4a and Equation 4b:

$$\begin{aligned} ATT &= E(Y_{i1}|D = 1) - E(Y_{i0}|D_i = 1) \\ &= (\beta_1 - \beta_0) X_{i1} + \left(\sigma_{1\mu} - \sigma_{0\mu}\right)\lambda_{i1} \end{aligned} \tag{5}$$

3.1.2 Quantile treatment effect model

Treatment effects models can identify causal relationships between variables and are widely used in empirical studies for policy evaluation. However, most of these studies are about the average effect between variables, while the effect on the distribution of variables is often neglected (Frölich and Melly, 2010). Indeed, sometimes the average treatment effect of a policy is not all that is of interest, and policymakers are often more concerned with the heterogeneous effects of a policy on the entire distribution of a group at different quantiles. For example, we may want to understand the differentiated effects of digital technology adoption on various income groups, especially its impact on the tail end of the income distribution. To address this, this study employs a QTE model to analyze the heterogeneous income effects of digital technology adoption in detail, aiming to explain its impact on income disparities among farm households.

1. Conditional quantile treatment effect

First, the conditional quantile treatment effect (CQTE) model is employed in this study. $Digital_i$ is defined as a dummy variable for the adoption of digital technology by household i, where $Digital_i = 1$ indicates that household i receives the intervention, while $Digital_i = 0$ signifies no intervention received. We use Y_{i1} and Y_{i0} to, respectively, denote the potential income levels of household i when receiving and not receiving the treatment. Notice that for each household, we can only observe $Y_i\left(Digital_i\right)$ while $Y_i\left(1-Digital_i\right)$ is counterfactual. Thus, the observed outcome variable Y_i can be expressed as follows:

$$Y_i = Y_{i1}Digital_i + Y_{i0}\left(1-Digital_i\right) \tag{6}$$

Using the linear quantile regression method to analyze the factors affecting the potential income of farm households, the determinants equation of potential income can be represented as follows:

$$Y_{i,Digital} = \theta_\tau Digital_i + X_i^{'}\beta_\tau + \varepsilon_i, Q_{\varepsilon_i}(\tau) = 0 \tag{7}$$

where θ_τ represents the treatment effect of digital technology adoption at the τth quantile, β_τ denotes the estimated parameter for the covariate at the τth quantile, and $Q_{\varepsilon_i}(\tau)$ is the τth quantile of the unobservable random variable ε_i. If both *Digital* and X are exogenous, $\varepsilon\perp(Digital, X)$, implying that *Digital* is randomly assigned and independent of Y, then we can derive:

$$Q_{Y|X,Digital}\ (\tau) = \theta_\tau Digital + X^{'}\beta_\tau \tag{8}$$

where $Q_{Y|X,Digital}\ (\tau)$ represents the τth quantile of Y given X and *Digital*. The estimation of the unknown parameters θ_τ and β_τ can be obtained using the method provided by Koenker and Bassett (1978).

$$\left(\hat{\theta}_\tau, \hat{\beta}_\tau\right) = \text{argmin}_{\theta,\beta} \sum\nolimits_{i=1}^{N} \rho_\tau\left(Y_i - \theta_\tau Digital_i - X_i^{'}\beta_\tau\right) \tag{9}$$

where N is the number of observations, $\rho_\tau(u) = u\left(\tau - I\left(u<0\right)\right)$ is the check function and $I(\cdot)$ is the indicator function. The coefficient θ_τ estimated using the above method is the CQTE.

However, potential endogeneity issues may arise between the adoption of digital technology by farm households and their household income, where the treatment variable (*Digital*) could be endogenous, rendering the hypothesis of $\varepsilon\perp(Digital, X)$ invalid. In such cases, the above method fails to achieve causal identification. Following Abadie et al. (2002), we employ a binary instrumental variable (IV) to estimate the CQTE under endogeneity:

$$\left(\hat{\theta}_\tau^{IV}, \hat{\beta}_\tau^{IV}\right) = \text{argmin}_{\theta,\beta} \sum\nolimits_{i=1}^{n} \hat{W}_i^{AAI}\rho_\tau\left(Y_i - \theta_\tau Digital_i - X_i^{'}\beta_\tau\right) \tag{10}$$

$$\hat{W}_i^{AAI} = 1 - \frac{Digital_i\left(1-IV_i\right)}{1-Pr\left(IV_i=1\mid X_i\right)} - \frac{\left(1-Digital_i\right)IV_i}{\Pr\left(IV_i=1\mid X_i\right)} \tag{11}$$

2. Unconditional quantile treatment effect

The CQTE model can unveil the impact of digital technology on income distribution for groups with similar characteristics (Firpo et al., 2009). However, policymakers may be more interested in understanding the unconditional marginal effects of digital technology on the entire income distribution, irrespective of individual characteristics, both before and after implementation, known as the unconditional quantile treatment effect (UQTE).

The QTE is defined as the difference between the inverse cumulative distribution functions for different treatment states at quantile τ (Doksum, 1974). The mathematical expression for QTE can be formulated as follows:

$$\Delta_\tau = F_{Y_1}^{-1}(\tau) - F_{Y_0}^{-1}(\tau) \tag{12}$$

where Y_1 and Y_0 represent the outcome variables in two states (subscript 1 for accepted treatment; subscript 0 for non-accepted treatment). The estimation of UQTE essentially revolves around obtaining Equation 12. Following conventional methodology, the CQTE can be estimated first:

$$\Delta_\tau\ (x) = F_{Y_1|X}^{-1}(\tau\ |x\ ) - F_{Y_0|X}^{-1}(\tau\ |x\ ) \tag{13}$$

The UQTE is then obtained through integration. However, the conditional quantile function does not adhere to the conditional expectation iteration rule, implying that the consistent estimation of Equation 12 cannot be obtained by integrating Equation 13 over x. To address this issue, this study employs a semi-parametric UQTE estimation method based on propensity scores (Firpo, 2007). This approach circumvents the use of the conditional quantile function and instead calculates the unconditional quantile function directly through propensity score weighting. The underlying assumption of this identification strategy is that, given the covariates X, the treatment variable is exogenous and satisfies the common support condition (given X, the probability of receiving treatment is neither 0 nor 1). Under this assumption, Equations 12, 14 can be used to estimate the UQTE.

$$\left(\hat{\alpha}, \hat{\Delta}\right) = \underset{\alpha,\Delta}{argmin} \sum\nolimits_{i=1}^{N} \hat{W}_{j,i}\rho_\tau\left(Y_i - \alpha - Digital_i\Delta\right) \tag{14}$$

where $j = 0, 1, \hat{W}_{1,i} = \frac{Digital_i}{N\hat{p}(X_i)}, \hat{W}_{0,i} = \frac{(1-Digital_i)}{N(1-\hat{p}(X_i))}$, $p\left(x\right) = \Pr\left(Digital_i = 1\middle|X_i = x\right)$ is the propensity score function.

In the presence of endogeneity in treatment variables, unbiased estimation of parameters cannot be achieved through the above method, and instrumental variables must be employed to identify causal effects. According to Frölich and Melly (2013), under the condition of given covariates X, if binary instrumental variables are independent of the outcome variable and satisfy the common support condition, Equation 14 can be extended:

$$\left(\hat{\alpha}_{IV}, \hat{\Delta}_{IV}\right) = \text{argmin}_{\alpha,\Delta} \sum\nolimits_{i=1}^{N} \hat{W}_i^{FM}\rho_\tau\left(Y_i - \alpha - IV_i\Delta\right) \tag{15}$$

$$\hat{W}_i^{FM} = \frac{IV_i - \Pr\left(IV_i=1\mid X_i\right)}{\Pr\left(IV_i=1\mid X_i\right)\left[1-Pr\left(IV_i=1\mid X_i\right)\right]}\left(2Digital_i - 1\right) \tag{16}$$

3.1.3 Endogeneity issues

Two potential sources of endogeneity may exist in this study. First, there may be a reverse causality between digital technology adoption and rural household income, whereby high-income families may be more inclined to adopt digital technology. Second, unobservable factors or omitted variables may bias the empirical estimates. To address these concerns, this study employs an exogenous instrumental variable to mitigate the problems of reverse causality and omitted variables, while controlling for regional fixed effects.

Specifically, regional fixed effects are incorporated into all econometric models used in this study to account for unobservable or omitted factors at the regional level (note: Individual fixed effects are not controlled, as they would absorb the variability of the key explanatory variable, i.e., digital technology adoption). Subsequently, to tackle potential endogeneity more rigorously, all empirical analyses are conducted using IV estimation.

3.2 Data and variables

3.2.1 Data collection

The data used in this study are sourced from a rural household survey conducted by the research group in Changji Hui Autonomous Prefecture (hereinafter referred to as Changji Prefecture), Xinjiang Uygur Autonomous Region, in 2023. Xinjiang, located in the northwest frontier of China, is not only the largest ethnic minority autonomous region in area but also one of the regions with the most diverse ethnic compositions. Currently, 56 ethnic groups live in Xinjiang, with ethnic minorities accounting for 57.76% of the total population. Among them, the Uygur, Han, Kazakh, and Hui each have populations exceeding one million. Its multi-ethnic cohabitation model is similar to that of other border ethnic regions in China, but with a more complex ethnic structure and a longer history of ethnic interaction, providing a unique perspective for studying the promotion and inclusiveness of digital technologies in a pluralistic social environment. Meanwhile, Xinjiang has actively promoted the construction of digital villages in recent years. By 2023, the 4G network coverage rate of administrative villages in the region had exceeded 99%, 11.8% of counties had built agricultural and rural data centers, and more than one-fifth of counties and cities had developed information terminals, technical products, and mobile internet application software tailored to the characteristics of agriculture, rural areas, and farmers (such as Good Places in Barkol, Credit Countryside, Agricultural Technology Treasure, etc.),[5] creating favorable conditions for exploring the application effects of digital technologies in rural areas of ethnic regions.

Changji Prefecture is home to 42 ethnic groups, among which the Han, Hui, Kazakh, and Uygur predominate, constituting a microcosm of Xinjiang's ethnic composition. More importantly, as one of the pilot regions for digital village construction in Xinjiang, it has pioneered efforts in advancing digital rural development within ethnic minority areas. According to the Xinjiang Digital Village Development Report (2023), four of the seven counties (county-level cities) under Changji Prefecture's jurisdiction have digital village development indices exceeding the Xinjiang average, and Manas County has been selected as a national digital village pilot. Notably, the area demonstrates significant gradient disparities in digital village development levels, ranking as follows among the 73 counties in Xinjiang: Changji City (1st), Jimusaer County (10th), Mori Kazakh Autonomous County (16th), Manas County (17th), Hutubi County (37th), Qitai County (43rd), and Fukang City (47th). This gradient characteristic precisely reflects the unevenness of the digitalization process in ethnic regions, thereby preventing the research sample from overrepresenting developed areas.

Changji Prefecture is also a key advocate for digital agriculture in Xinjiang. As one of Xinjiang's major grain-producing areas, it has over seven million mu of arable land, with annual agricultural exports accounting for one-fourth of Xinjiang's total. It serves as the second-largest modern seed production base nationwide and the largest milk source supply base in Xinjiang. Additionally, it has established itself as a crucial national production and supply base for commercial grain, commercial cotton, sauce tomatoes, and wine grapes. Such a diverse and robust agricultural, industrial foundation provides abundant application scenarios for digital technologies. Changji Prefecture has been actively exploring the integrated application of digital technologies across the entire agricultural chain and all scenarios, focusing on propelling agricultural production toward intelligence. These efforts have accumulated practical experience in digitally enabling agricultural modernization and rural revitalization.

Data collection adopts a method combining multi-stage stratified sampling with random sampling. To comprehensively portray the digital transformation in rural areas of Changji Prefecture, the research group first sorted counties (county-level cities) according to the level of digital village development from high to low, and selected four counties (county-level cities) ranking 1st, 4th, 5th, and 7th in Changji Prefecture as the survey areas. In 2022, the digital village development indices of the sampled areas were: Changji City (74.38), Manas County (41.25), Hutubi County (27.20), and Fukang City (25.05), with the first two above the average level in Xinjiang and the latter two below it. In this way, regions with different levels of digital rural development were selected more evenly to avoid over-representation of more developed or highly digitized counties. Second, the per capita GDP of the sampled counties belonged to three grades in Changji Prefecture: high (Fukang City ranked 2nd), medium (Manas County ranked 5th), and low (Hutubi County ranked 6th, Changji City ranked 7th), with more focus on relatively lagging areas. By jointly considering the levels of digital village development and economic development in different regions, the selected sample areas are both representative and comprehensive.

Subsequently, two townships were randomly selected within each survey area, and two administrative villages were randomly chosen in each township. Finally, based on the complete rosters provided by village committees, households were randomly sampled within each sample village. Data collection was conducted through face-to-face interviews and questionnaires. The research team consisted of members from this project, including seven individuals of Xinjiang origin (including ethnic minorities such as Uygur, Kazakh, and Hui), ensuring cultural understanding and language communication abilities. All team members received standardized training. Mandarin was the primary language used during the survey, with ethnic minority team members providing dialect translation for respondents lacking Mandarin proficiency. Prior to interviews, all participants were fully informed

5 Data source: Research Report on Digital Village Development in Xinjiang (2023). https://nynct.xinjiang.gov.cn/xjnynct/c113576/202310/dda5e3edeaa54656b5b23df1fa00af04.shtml.

of the research objectives, voluntary participation policy, and confidentiality measures, and informed consent was obtained. This survey strictly adhered to the principle of anonymity. A total of 783 questionnaires were collected, and after excluding those with missing data or no response, 774 valid questionnaires remained, resulting in an effective response rate of 98.85 %.

3.2.2 Variables and descriptive statistics

1. Dependent variable

The dependent variable in this study is the logarithm of annual total household income (Zhou et al., 2020). Total household income comprises agricultural income, non-farm business income, wage income, property income, and transfer income.[6]

2. Independent variables

Unlike previous studies (Hong and Chang, 2020; Xie et al., 2023; Zhou and Deng, 2023) that directly utilize internet access as a measure of farmers' adoption of digital technology, this study constructs a measurement indicator for farmers' adoption of digital technology based on three specific application dimensions: digital production, digital information processing, and digital marketing.

Farm households' participation in digital production is assessed by inquiring whether agricultural inputs are purchased through online channels, whether smart agriculture technologies such as plant protection drones, intelligent cotton-picking machines, and integrated smart irrigation systems are used during the agricultural production process, and whether agriculture-related applications (apps) are utilized. If a household responds "yes" to at least one of these inquiries, a dummy variable for digital production is assigned a value of 1; otherwise, it is assigned a value of 0.

The participation in digital information processing is examined by inquiring whether the household utilizes smartphones or computers for online learning and whether they can gather, analyze, and apply information collected from the internet. When a household responds "yes" to at least one of these questions, a dummy variable for digital information processing is assigned a value of 1; otherwise, it is assigned a value of 0.

The participation of farm households in digital marketing is assessed by inquiring whether they engage in e-commerce operations and whether they utilize the internet for the purpose of promoting their products or services. When a household responds "yes" to at least one of these questions, a dummy variable for digital marketing is assigned a value of 1; otherwise, it is assigned a value of 0.

Furthermore, if farm households participate in any of the digital production, digital information processing, or digital marketing activities, they are considered having adopted digital technology. Based on the sample data, the overall adoption rate of digital technology is 58.27%. Among these, the proportion of households engaging in digital production is 29.07%, participating in digital marketing is 21.96%, and engaging in digital information processing is 45.48%. These data indicate that farm households in ethnic minority areas have a lower adoption rate of digital technology, particularly in the fields of digital production and marketing, suggesting considerable potential for improvement.

3. Instrumental variable

In this study, both the ESR model and the QTE model require the introduction of a suitable instrumental variable (IV). The effectiveness of IV relies on two key conditions: (1) it must be correlated with the digital technology adoption of farm households; (2) it must have no direct effect on household income except through influencing digital technology adoption. This study constructs an IV using households' responses to the survey question: "*Have you ever been publicized by government staff about online government service platforms*[7]*?*". The variable is defined as EGP (e-government promotion), where EGP = 0 if the household replies "unaware of relevant matters," and EGP = 1 otherwise.

First, the IV satisfies the relevance condition. The extent of promotion and popularization of e-government services serves as a critical indicator reflecting the local governance level of digital villages. Farmers' lack of awareness regarding online government service platforms often indicates a potential exposure to a more severe digital divide, which is closely related to their adoption of digital technology.

Second, the IV satisfies the exclusion restriction. It solely reflects whether households have been exposed to the promotional environment of online government service platforms, rather than their actual usage behavior of the platform. Merely being aware of the platform's existence (EGP = 1) does not alter resource allocation or income since the promotional activities themselves do not directly provide any functional services (such as subsidy applications or information inquiries). Households can only potentially benefit from actually using the platform (such as logging in to apply for subsidies, accessing information for decision-making), and such behaviors have already been incorporated into the measurement framework of the core explanatory variable, digital technology adoption. Therefore, the potential impact of EGP on income must be transmitted through digital technology adoption.

4. Control variables

Following previous studies (Ma et al., 2018; Zhu et al., 2021; Zheng et al., 2022; Cheng et al., 2024), this study controls for individual household head characteristics, family characteristics, and regional characteristics of farm households. Individual characteristics include gender, age, the square of age (according to the life cycle hypothesis of income, age may exhibit a non-linear relationship with income growth), educational attainment, and party membership status (Zhou et al., 2020). Household characteristics encompass the number of household members

6 Agricultural income encompasses earnings from crop cultivation, livestock farming, forestry, and fishing. Agricultural income and non-farm business income refer to revenue after deducting operating costs, excluding personal living expenses.

7 Such as "news + government service business" platforms like "Fuxiaobang" and "Mashangban".

TABLE 1 Descriptive statistics.

Variables	Definitions	Mean	S.D.
Outcome variables			
Income	Total household income level in 2022, unit: CNY; logarithm	10.9350	0.8664
Independent variable			
Digital technology adoption	1 if adopting any digital technology; 0 otherwise	0.5827	0.4934
Digital production	1 if participating in digital production; 0 otherwise	0.2907	0.4544
Digital marketing	1 if participating in digital marketing; 0 otherwise	0.2196	0.4143
Digital information processing	1 if participating in digital information processing; 0 otherwise	0.4548	0.4983
Instrumental variable			
E-government promotion	1 if the farm household has been informed about the online government service platform; 0 otherwise	0.4935	0.5003
Control variables			
Gender	Gender of household head: 1 = male; 0 = female	0.5711	0.4952
Age	Age of household head (in years)	48.6731	12.7451
Age2	Age squared/100	25.3130	12.8712
Low education	1 if the education level of the household head is junior high school or below; 0 otherwise	0.6408	0.4801
Secondary education	1 if the education level of the household head is senior high school or technical secondary school; 0 otherwise	0.2248	0.4177
High education	1 if the education level of the household head is college degree or above; 0 otherwise	0.1292	0.3356
Party	1 if household head is a Chinese Communist Party member; 0 otherwise	0.2016	0.4014
Members	Number of family members (in persons)	3.8941	1.4598
Han	1 = Han ethnic group; 0 = otherwise	0.3243	0.4684
Uygur	1 = Uygur ethnic group; 0 = otherwise	0.1667	0.3729
Hui	1 = Hui ethnic group; 0 = otherwise	0.1021	0.3029
Kazakh	1 = Kazak ethnic group; 0 = otherwise	0.3941	0.4890
Other minorities	1 = Other ethnic minorities (except those mentioned above); 0 = otherwise	0.0129	0.1130
Migration	1 if the farm household has migration experience; 0 otherwise	0.1150	0.3192
Land	Area of owned land (in acres)	17.7565	15.0515

In regression analysis, the reference group for educational attainment is the low education group, and the reference group for ethnicity is the Han ethnic group.

(Liu et al., 2024), ethnicity, migration experience, and land. Table 1 presents specific definitions and descriptive statistics of the above variables.

4 Empirical results and analysis of the impact of digital technology adoption on household income

This study employs an ESR model to examine the impact of digital technology adoption on farm household income (see Table 2). As discussed in Section 3, the FIML method is used for the joint estimation of the digital technology adoption decision Equation 1 and the farm household income Equations 3a, 3b. The results indicate that the LR test rejects the null hypothesis of independence between the selection and outcome equations at the 10% level. Both $ln\sigma_0$ and $ln\sigma_1$ are significantly different from zero at the 1% level, suggesting that unobservable factors simultaneously influence both the decision to adopt digital technology and household income. Therefore, correcting for selection bias is essential, making the use of the ESR model appropriate.

4.1 Drivers of digital technology adoption

The estimation results of the digital technology adoption selection equation are reported in column (1) of Table 2. First, the estimated coefficient for the instrumental variable (EGP) is significantly positive at the 1% level, consistent with theoretical expectations. Second, the Kleibergen–Paap rk LM statistic is significant at the 1% level, rejecting the null hypothesis of underidentification; the Cragg–Donald Wald F statistic is 50.46, which is greater than the critical value of 16.38, rejecting the null hypothesis of weak identification.

Among the control variables, age, educational attainment, party membership status, ethnicity, and owned land area

TABLE 2 ESR results for determinants of adoption of digital technology.

Variable	Income		
	Adoption	Adopters	Non-adopters
	(1)	(2)	(3)
Gender	0.1648	0.0585	−0.1392*
	(0.1098)	(0.0534)	(0.0721)
Age	0.0353	0.0505***	−0.0169
	(0.0303)	(0.0150)	(0.0196)
Age2	−0.0624**	−0.0673***	0.0105
	(0.0303)	(0.0166)	(0.0179)
Secondary education	0.3670***	0.0129	0.2482**
	(0.1372)	(0.0644)	(0.1082)
High education	0.9642***	0.0269	0.4291*
	(0.2202)	(0.0844)	(0.2344)
Party	0.3371**	0.0646	0.0270
	(0.1513)	(0.0609)	(0.1196)
Members	0.0899**	0.0365*	0.1127***
	(0.0436)	(0.0217)	(0.0284)
Uygur	−0.6456***	−0.2560**	0.1343
	(0.2396)	(0.1234)	(0.1466)
Hui	−0.4335	−0.0427	−0.0863
	(0.3112)	(0.1126)	(0.2172)
Kazak	−0.0811	−0.0952	0.1975
	(0.2154)	(0.0990)	(0.1398)
Other minorities	−0.3112	−0.0781	0.4115
	(0.4729)	(0.2426)	(0.3019)
Migration	0.0414	0.1325	0.0660
	(0.1944)	(0.0830)	(0.1375)
Land	0.0086*	0.0112***	0.0166***
	(0.0047)	(0.0020)	(0.0035)
E-government promotion	0.7456***		
	(0.1067)		
Constant	−0.9250	10.3143***	9.9936***
	(0.8432)	(0.3868)	(0.6044)
Village FE	YES	YES	YES
$ln\sigma_1/ln\sigma_0$		0.5245***	0.6294***
		(0.0182)	(0.0350)
ρ_1/ρ_0		−0.1631	−0.3600*
		(0.1276)	(0.1965)
First-stage F statistic (p-value)	44.05 (0.0000)		
Kleibergen–Paap rk LM (p-value)	42.174 (0.0000)		
Cragg-Donald Wald F statistic	50.46 [16.38]		
LR test of indep. eqns. (p-value)	3.48* (0.0620)		
Log likelihood	−1,022.42		
Obs.	774	774	774

(Continued)

TABLE 2 (Continued)

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Unless otherwise specified, values in parentheses are standard errors. Values in square brackets are critical values for the Stock-Yogo weak instrumental variable identification F-test at the 10% significance level.

significantly influence the adoption of digital technology by farmers. Specifically, the estimated coefficient for the square of age is significantly negative, indicating that, ceteris paribus, the likelihood of adopting digital technology initially increases with age but subsequently decreases. This trend may be attributed to individuals gaining more education and technical skills in the early stages of life, enhancing their capability to employ digital technology for economic activities. However, as individuals reach a certain critical age, further aging may result in diminished physiological or cognitive abilities, reducing both the scope and intensity of their economic engagement and consequently their use of digital technology. Thus, the relationship between age and the probability of adopting digital technology exhibits an inverted U-shape.

Households with more educated heads are more likely to adopt digital technology, as education enhances skills and expands knowledge, thereby increasing the probability of digital adoption. This finding aligns with the conclusions of Cai et al. (2022). Additionally, party membership of the household head exerts a significant positive impact on the adoption of digital technology, suggesting that party members can serve a demonstrative role in digital engagement. An increase in the number of household members also significantly promotes the adoption of digital technology. This may be due to larger households having more labor resources and opportunities for information exchange, facilitating the application of digital technology, which aligns with the findings of Hong and Chang (2020). Furthermore, households with more land resources are more inclined to adopt digital technology, indicating that abundant land enhances the motivation and demand for such adoption.

The estimated coefficient for the dummy variable representing Uygur ethnicity is significantly negative at the 1% level, indicating that Uygur farmers are less likely to adopt digital than Han farmers. While the coefficients for other minority ethnicity dummy variables are also negative, they lack statistical significance. These findings may indicate a more significant digital divide faced by minority farmers in adopting digital technology, potentially due to language barriers and differences in cognitive and acceptance levels toward digital technology, among other factors.

TABLE 3 Treatment effects of digital technology adoption on household income based on the ESR model.

Treatment variable	Mean outcomes (income)		ATT-ESR	Change (%)
	Adopters	Counterfactuals		
Digital technology adoption	11.4033	10.3593	1.0440***	10.08
	(0.0139)	(0.0234)	(0.0272)	
Digital production	11.4362	10.3018	1.1344***	11.01
	(0.0262)	(0.0372)	(0.0454)	
Digital information	11.4569	10.1966	1.2603***	12.36
	(0.0159)	(0.0269)	(0.0313)	
Digital marketing	11.6961	10.5082	1.1879***	11.30
	(0.0211)	(0.0361)	(0.0418)	

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Values in parentheses are standard errors. As the dependent variables in the ESR outcome equations are income in logarithm form, the predictions are also given in log forms.

4.2 Determinants of household income among adopters and non-adopters

The estimation results of the digital technology adoption outcome equation are reported in columns (2) and (3) of Table 2. Overall, there are noticeable differences in the determinants of household income between adopters and non-adopters of digital technology, highlighting the presence of heterogeneity in the sample.

The impact of educational attainment on income is significantly positive for non-adopters, while it is not significant for adopters. This could be attributed to the fact that, in the absence of digital technology adoption, individuals with higher levels of education are more likely to transition to high-paying livelihood strategies (Zhang et al., 2019), thereby contributing to increased household income. Conversely, the impact of educational attainment is no longer statistically significant among adopters of digital technology. This may be due to the fact that digital technology, as a skill-biased technological advancement in itself, enhances the diversity of livelihood strategies available to farmers (Zhou et al., 2020), thereby reducing the influence of educational attainment as a determinant of income.

For the adopters of digital technology, the estimated coefficient of the Uygur dummy variable is significant and negative. This result may reflect additional barriers faced by Uygur farmers in effectively utilizing digital technology, such as language and cultural differences, which may limit their ability to benefit from digital technology. Conversely, there is no such effect for farmers who have not adopted digital technologies, possibly because the income of these farmers is mainly influenced by traditional factors, independent of ethnicity.

Furthermore, both household size and land area have a significant positive impact on household income for both adopters and non-adopters. This implies that labor resources and land endowment, as two fundamental production factors for farmers, are crucial determinants of income, regardless of the adoption of digital technology.

4.3 Average treatment effects of digital technology adoption on household income

Based on the estimation results from the ESR model, the actual household income and counterfactual household income are calculated. ATT of digital technology adoption on household income is estimated using Equation 5, as shown in Table 3. The positive ATT indicates that the adoption of digital technology and its various dimensions has a significant positive impact on household income, thus validating Hypothesis 1. Taking the adoption of digital technology as an example, the expected income for adopters is 11.40, while the counterfactual household income for non-adopters is 10.36, resulting in an ATT of 1.04. This implies that if adopters of digital technology did not adopt it, their expected income would decrease by 10.08%.

4.4 Mechanism analysis

To explore the potential mechanisms through which digital technology adoption promotes an increase in household income, we divide the sources of income into agricultural income, non-agricultural income,[8] and property income, which serve as the dependent variables. The estimation results of the digital technology adoption outcome equation are presented in Table 4, revealing several intriguing observations.

First, male household heads exhibit a significant negative impact only on the non-agricultural income of non-adopters of digital technology, revealing a primary source of the negative effect on household income by male household heads, as mentioned in Section 4.2. Moreover, significant heterogeneity is observed in the estimated coefficients of age and its squared term for agricultural income and non-agricultural income among adopters. Specifically,

8 In this article, non-agricultural income is defined as the sum of wage income and non-farm business income. It is noteworthy that property income is not included in the category of non-agricultural income to provide a clearer analysis of the strategies and behaviors of households regarding the allocation of key production factors, namely, family labor and land.

TABLE 4 ESR results for determinants of agricultural, non-agricultural, and property income of adopters and non-adopters.

Variables	Agricultural income		Non-agricultural income		Property income	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Gender	−0.6568	−0.2345	0.0585	−0.1392*	−0.6279	0.3662
	(0.5043)	(0.4323)	(0.0534)	(0.0721)	(0.4087)	(0.4278)
Age	−0.4171***	−0.0540	0.0505***	−0.0169	−0.0149	0.1096
	(0.1366)	(0.1165)	(0.0150)	(0.0196)	(0.1169)	(0.1212)
Age2	0.5715***	0.0355	−0.0673***	0.0105	0.0487	−0.1039
	(0.1436)	(0.1066)	(0.0166)	(0.0179)	(0.1311)	(0.1064)
Secondary education	−2.2018***	−0.3214	0.0129	0.2482**	0.3602	1.2538*
	(0.6135)	(0.6664)	(0.0644)	(0.1082)	(0.4918)	(0.6822)
High education	−5.3899***	−1.1144	0.0269	0.4293*	2.6777***	1.7489
	(0.8311)	(1.4968)	(0.0844)	(0.2344)	(0.6966)	(1.3674)
Party	−1.6181***	0.7222	0.0646	0.0270	−0.6279	0.3662
	(0.6066)	(0.7039)	(0.0609)	(0.1196)	(0.4087)	(0.4278)
Members	−0.2738	0.3552**	0.0365*	0.1127***	−0.0543	−0.1477
	(0.2021)	(0.1648)	(0.0217)	(0.0284)	(0.1760)	(0.1593)
Uygur	0.5403	−0.2727	−0.2561**	0.1344	4.7047***	0.7991
	(1.0975)	(0.8262)	(0.1234)	(0.1466)	(0.9746)	(1.0184)
Hui	1.3569	−1.2935	−0.0427	−0.0864	−0.3334	−0.0525
	(1.1494)	(1.2765)	(0.1126)	(0.2172)	(0.8898)	(1.3203)
Kazak	−0.8063	0.3165	−0.0951	0.1976	4.3723***	1.6670**
	(0.9549)	(0.8528)	(0.0990)	(0.1398)	(0.7827)	(0.7501)
Other minorities	1.0880	1.9887	−0.0781	0.4115	−1.2349	−0.6060
	(2.2754)	(1.8314)	(0.2426)	(0.3019)	(1.9333)	(2.3674)
Migration	1.2854	0.8894	0.1325	0.0660	−0.0424***	0.0987***
	(0.8222)	(0.8194)	(0.0830)	(0.1376)	(0.0162)	(0.0219)
Land	0.0723***	0.0336	0.0112***	0.0166***	0.1266	−0.7091
	(0.0195)	(0.0205)	(0.0020)	(0.0035)	(0.4917)	(0.7342)
Constant	16.4500***	1.0921	10.3142***	9.9935***	5.9174*	4.5148
	(3.6273)	(3.8535)	(0.3868)	(0.6045)	(3.1893)	(4.1207)
Village FE	YES	YES	YES	YES	YES	YES
$ln\sigma_1/ln\sigma_0$	5.8552*** (0.2280)	3.6637** (0.1444)	0.5137*** (0.0177)	0.6275*** (0.0366)	3.7633*** (0.2157)	3.2681*** (0.3327)
ρ_1/ρ_0	−0.9929***	0.0132	−0.1503	−0.4308***	−0.4453	0.4801
	(0.0042)	(0.3243)	(0.1262)	(0.1741)	(0.2167)	(0.3309)
LR test of indep. eqns.	35.77*** [$p = 0.0000$]		3.48* [$p = 0.0620$]		3.55* [$p = 0.0594$]	
Obs.	774	774	774	774	659	659

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Values in parentheses are standard errors. Values in square brackets are p-values.

in the agricultural income model, the estimated coefficient of age is negative and significant, while the coefficient of its squared term is positive and significant. This suggests an accelerating upward trend in agricultural income as the age of the household head increases. Conversely, in the non-agricultural income model, the coefficient of age is positive and significant, while the coefficient of its squared term is negative and significant. This indicates an inverted U-shaped relationship between age and non-agricultural income. This heterogeneity may stem from the differential impact of digital technology adoption on farmers of different age groups. Younger farmers may be more proficient in utilizing digital technology to engage in non-agricultural employment or entrepreneurship, while as they age, they may gradually withdraw from non-agricultural work. Simultaneously, older farmers, leveraging their accumulated agricultural knowledge and experience, may potentially utilize digital technology more effectively to optimize their agricultural production and management activities.

In terms of educational attainment, for agricultural income, among the group of digital technology adopters, educational attainment has a significant negative effect, indicating that adopters with higher educational attainment are less likely to engage in agricultural production and business. Regarding non-agricultural income, among non-adopters, those with higher education levels are more likely to transition to the non-agricultural sector, thereby increasing their non-agricultural income. However, among adopters, the impact of educational attainment on non-agricultural income is no longer significant, aligning with the analysis on the impact of educational attainment in Section 4.2. These findings potentially reflect the possibilities offered by digital technology adoption for households to diversify their livelihood strategies, promoting a shift from a traditional agricultural-based livelihood model to a diversified income source strategy.

Regarding agricultural income among non-adopters of digital technology, the number of household members shows a significant positive effect, while for adopters, this factor no longer exhibits a significant impact. This disparity may be attributed to the reduction in the reliance on traditional labor inputs in agricultural production and management brought about by the adoption of digital technology.

Finally, the coefficient of the Uygur dummy variable is negative and significant for non-agricultural income of adopters, a result that provides a concrete explanation for the observation in Section 4.2 that the possible barriers faced by Uygur farmers in effectively using digital technologies to increase their income, compared to Han farmers, are mainly reflected in their lack of ability to use digital technologies to increase their non-agricultural income. In addition, the coefficient of the Kazak dummy variable is positive and significant for property income for both adopters and non-adopters, the traditional engagement of Kazak households primarily in livestock production, resulting in a lower dependency on land cultivation. Therefore, they are more likely to engage in land transfer, thereby obtaining more income from property.

The estimation results in Panel A of Table 5 reveal that, compared to the scenario where digital technology is not adopted, adopters achieve a significant increase of 35.40% in agricultural income and 10.08% in non-agricultural income. However, in terms of property income, the ATT value for digital technology adoption is −3.95, indicating a significant decrease in property income for adopting households. Considering that property income for farm households in ethnic minority areas primarily comes from land leasing, this result may suggest that adopters are more inclined to retain their cultivated land for self-operated farming rather than leasing it out. In Panels B, C, and D, we, respectively, employ digital production, digital information processing, and digital marketing as explanatory variables and estimate their effects on agricultural income, non-agricultural income, and property income of households. The results indicate that all three dimensions of digital technology adoption have significant positive effects on agricultural income and non-agricultural income, thereby confirming Hypotheses 2 and 3. Simultaneously, these three dimensions all have a negative impact on property income. Particularly noteworthy is that digital technology adoption, along with its various dimensions, greatly enhances the agricultural operating income of households. Despite the intuitive notion that households choosing to remain in the agricultural sector might reduce opportunities for non-agricultural employment and potentially influence non-agricultural income, the empirical findings of this study suggest that digital technology effectively mitigates this potential contradiction. As mentioned earlier, for adopting households, the positive impact of household size on agricultural income is no longer significant (see Table 4). By reducing the dependence on labor-intensive traditional agricultural production, the adoption of digital technology does not have a negative impact on non-agricultural income. Instead, it promotes diversified income growth for households. However, the relatively lower magnitude of improvement in non-agricultural income also indicates that although the digital transformation has shown initial effectiveness, there is still considerable room for enhancing the promotion of households' choices for diversified income sources and high-income livelihood strategies, necessitating further policy support.

4.5 Robustness check

4.5.1 Results of marginal treatment effects

This study first employs the marginal treatment effect (MTE) approach for robustness checks. Building upon the framework proposed by Heckman and Vytlacil (2005) and Heckman (2010), the MTE method is utilized to estimate the impact of digital technology adoption on household income within a generalized Roy model framework. Identification of the MTE relies on a large common support set. Figure 3 illustrates the distribution of propensity scores for both adopters and non-adopters of digital technology, indicating a substantial overlap in propensity scores between the two groups. This common support set spans a wide range, covering almost the entire range between 0 and 1.

Figure 4 presents the MTE curve, with the shaded area representing the 95% confidence interval computed using the bootstrap method. The MTE curve of household income demonstrates a monotonic downward trend, indicating that, as resistance to digital technology adoption increases, the positive impact of digital technology adoption on household income gradually diminishes.

Following Cornelissen et al. (2018), the treatment effects of digital technology adoption on household income are computed using the MTE, as shown in Table 6. The estimates of ATE, ATT and ATUT are all statistically significant and positive, confirming the positive impact of digital technology adoption on household income.

4.5.2 Estimation of the treatment effects model

Subsequently, we report the regression results of the treatment effects model based on maximum-likelihood estimation (MLE), as shown in Table 7. In the treatment equation, the estimated

TABLE 5 Estimates of effect mechanisms.

Category	Mean outcomes		ATT-ESR	Change (%)
	Adopters	Counterfactuals		
Panel A: Impact of digital technology adoption				
Agricultural income	6.1583	4.5481	1.6102***	35.40
	(0.1134)	(0.1350)	(0.1763)	
Non-agricultural income	11.4032	10.3593	1.0439***	10.08
	(0.0139)	(0.0234)	(0.0272)	
Property income	5.0630	9.0124	−3.9494***	−43.82
	(0.1659)	(0.1596)	(0.2302)	
Panel B: Impact of digital production				
Agricultural income	10.7694	3.2269	7.5426***	233.74
	(0.0403)	(0.1753)	(0.1798)	
Non-agricultural income	11.4361	10.3019	1.1342***	11.01
	(0.0262)	(0.0371)	(0.0455)	
Property income	2.8512	10.1121	−7.2609***	−71.80
	(0.2173)	(0.2102)	(0.3023)	
Panel C: Impact of digital information				
Agricultural income	5.3101	2.5330	2.7771***	109.64
	(0.1753)	(0.1542)	(0.2335)	
Non-agricultural income	11.4569	10.1967	1.2602***	12.36
	(0.0159)	(0.0269)	(0.0313)	
Property income	5.4728	7.2618	−1.7890***	−24.64
	(0.2003)	(0.1600)	(0.2563)	
Panel D: Impact of digital marketing				
Agricultural income	8.4015	3.0174	5.3840***	178.43
	(0.2895)	(0.2192)	(0.3631)	
Non-agricultural income	11.6961	10.5083	1.1878***	11.30
	(0.0211)	(0.0361)	(0.0418)	
Property income	4.0452	7.7856	−3.7404***	−48.04
	(0.2834)	(0.2490)	(0.3773)	

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Values in parentheses are standard errors. As the dependent variables in the ESR outcome equations are income in logarithm form, the predictions are also given in log forms.

coefficients for variables such as squared age, education level, family size, and ethnicity (Uygur) are almost consistent with the results reported in Table 2. In the outcome equation, the regression coefficient of digital technology adoption on household income is 1.09 and statistically significant at the 1% level, indicating that digital technology adoption indeed improves household income, which is broadly consistent with the estimation results of the ESR model.

4.5.3 Placebo test

To further rule out the interference of unobservable factors and verify that the impact of digital technology adoption on rural household income is not driven by omitted variables, a placebo test with randomly reassigned treatment groups is employed. If confounding factors simultaneously affecting both the treatment variable and the outcome variable exist, an increase in household income might still be observed without actual treatment intervention. Accordingly, this study constructs pseudo-treatment experiments and conducts placebo tests with random sampling 500 times and 1,000 times. As illustrated in Supplementary Figures S1, S2, the distribution of coefficient kernel density functions and corresponding p-value distributions generally conform to a normal distribution with a mean of zero, and all pseudo-coefficients are far smaller than the true regression coefficients (marked by dashed lines in the figures), revalidating the reliability of the conclusions.

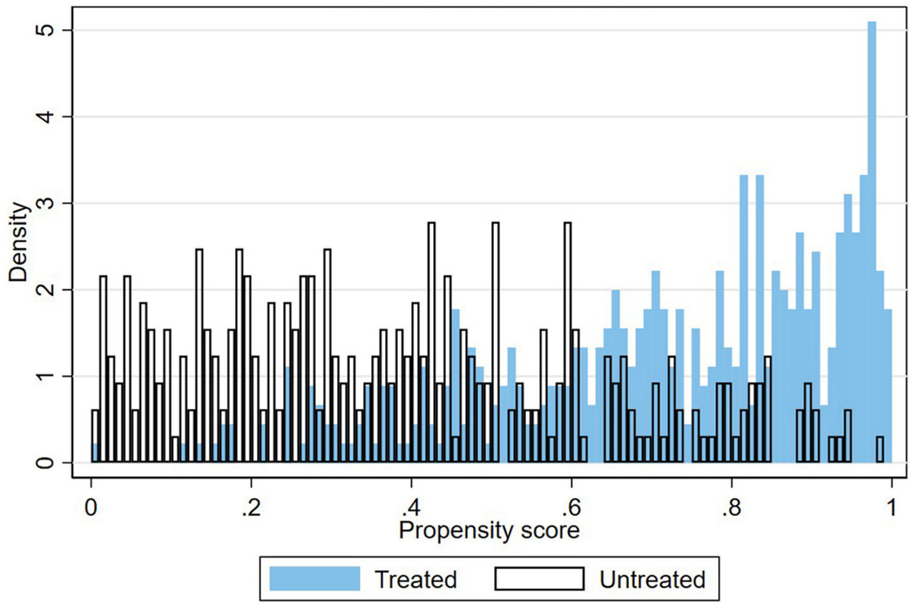

FIGURE 3
Common support. The figure plots the frequency distribution of the propensity score by adopters and non-adopters. The propensity score is predicted from the baseline first-stage regressions.

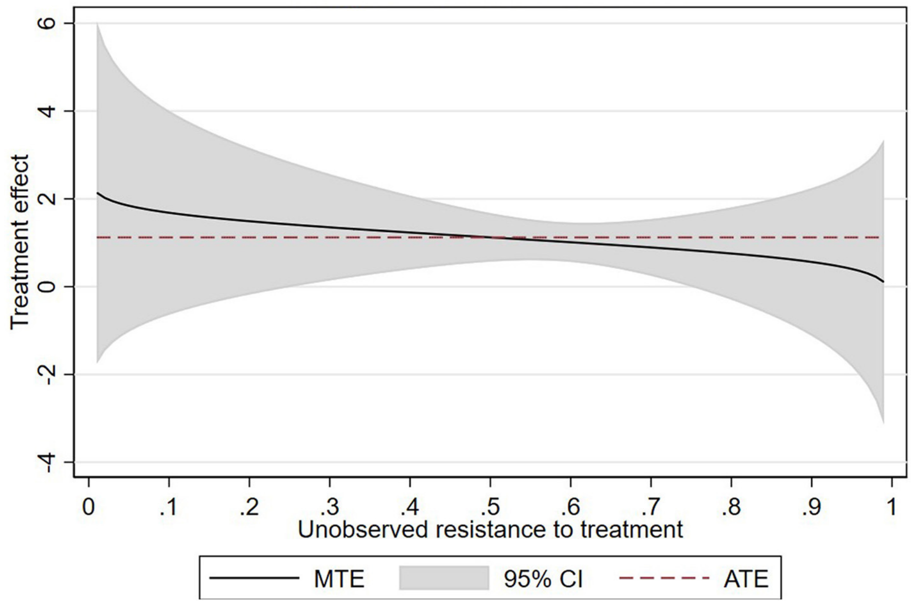

FIGURE 4
Marginal treatment effect of digital technology adoption on farm household income.

4.5.4 Analysis of digital adoption intensity

We further replace the core explanatory variable with continuous intensity indicators for robustness testing. First, based on respondents' answers to the question in the survey regarding "*How proficient is your household in using digital devices such as smartphones and computers*," we constructed a digital usage depth index (Usagedepth). Specifically, "*limited to communication and chatting*" (digital communication) is coded as 1, "*independent browsing, searching, and filtering of information/data*" (digital information gathering) as 2, and "*content creation (videos, audio, images, articles)*" (digital creation) as 3. This ordinal variable reflects the gradient of household digital proficiency through hierarchical coding, thereby characterizing the intensity of digital technology adoption. Second, online shopping frequency (E-shopping) serves as an additional proxy, with "never used," "annually," "every few months," "monthly," and "weekly" are coded 0 through 4.

TABLE 6 ATEs of digital technology adoption on household income based on the MTE model.

Category	Income of farm household
ATE	1.1225***(0.2819)
ATT	1.1575*(0.6945)
ATUT	1.0732**(0.5478)
Heterogeneity test (p-value)	0.0000
Obs.	774

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Values in parentheses are standard errors.
ATE, the average treatment effect; ATT, the average treatment effect on the treated; ATUT, the average treatment effect on the untreated.

Given that online shopping involves information retrieval, identity authentication, online interaction, and payment, its frequency acts as an effective proxy for deep digital technology use (Li et al., 2023).

As these continuous variables are incompatible with the ESR model used in the baseline regression, both OLS and Two-Stage Least Squares (2SLS) estimations are employed (see Supplementary Table S1). Results show that estimated coefficients for both digital adoption intensity indicators are significantly positive at the 1% level, indicating that higher digital adoption intensity amplifies the income-promoting effect of digital technologies and further validates the robustness of the study's conclusions.

4.5.5 Generalizability test via replacement sample

To assess the generalizability of the research findings in other ethnic minority regions, this study further validates using data from the 2020 China Rural Revitalization Survey (CRRS). The CRRS covers nine provinces, including Guangdong, Zhejiang, Shandong, and the Ningxia Hui Autonomous Region. Ningxia, along with Xinjiang, is an ethnic minority autonomous region with comparable rural digitalization policy backgrounds and socio-economic characteristics. Thus, the subset of Ningxia is utilized as supplementary data in this article.[9]

Although the CRRS provides the necessary variables of household income, head of household individual characteristics, and household features, it does not survey digital technology applications of households in agricultural production and management. As a proxy, a digital use index (Digitaluse) is constructed from two survey items: whether a smartphone is used and whether its functions are perceived as difficult to operate. The values are assigned as 0 = not in use, 1 = somewhat difficult, used only for calls, 2 = moderately difficult, 3 = not difficult.[10] Both OLS and 2SLS instrumental variable methods are employed, with regression results reported in

TABLE 7 Robustness check based on the treatment effects model.

Variables	Treatment equation		Outcome equation	
	Coeff.	Std. err.	Coeff.	Std. err.
Adoption			1.0854***	0.1062
Gender	0.1560	0.1098	−0.0240	0.0449
Age	0.0366	0.0308	0.0164	0.0109
Age2	−0.0643**	0.0308	−0.0245**	0.0109
Secondary education	0.3732***	0.1374	0.0966*	0.0580
High education	1.0109***	0.2231	0.1066	0.0835
Party	0.3307**	0.1518	0.0464	0.0580
Members	0.0940**	0.0437	0.0714***	0.0177
Uygur	−0.6342***	0.2423	−0.0703	0.0955
Hui	−0.4233	0.3111	−0.0348	0.1075
Kazak	−0.0629	0.2154	0.0347	0.0850
Other minorities	−0.3096	0.4864	0.1567	0.1952
Migration	0.0393	0.1935	0.1493**	0.0756
Land	0.0093*	0.0048	0.0118***	0.0018
E-government promotion	0.7495***	0.1061		
Constant	−0.9790	0.8556	9.6627***	0.3116
Village FE	YES		YES	
ρ	−0.3042***	0.0970		
LR test ($H_0: \rho = 0$)	7.19***			
Obs.	774		774	

***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Supplementary Table S2. The results demonstrate that digital application significantly enhances household income levels, aligning with the empirical results based on the survey data in this study. This suggests that the conclusions of this study exhibit certain external validity and generalizability, providing empirical evidence for extension to other ethnic minority rural areas.

5 Income distribution effects analysis

Another issue of interest in this study is how digital technology adoption affects income disparity among farm households. This question cannot be addressed using regression methods based on average effects. Next, we employ a QTE model to assess the heterogeneous impact of digital technology adoption on households at different income levels.

The estimates of CQTE are presented in Table 8. The results show that in both the exogenous CQTE model and the endogenous CQTE model, the income-enhancing effects of digital technology adoption reveal a U-shaped trend as income quantiles increase.

9 CRRS selected sample counties (districts) in Ningxia Hui Autonomous Region, including Huinong District, Yanchi County, Helan County, Pengyang County, and Haiyuan County, with a total of 393 households.

10 Given that only 39 rural households did not use smartphones, which is far smaller than the number of households using smartphones, this sample is not suitable for using binary variables.

TABLE 8 Conditional quantile treatment effects of digital technology adoption.

Quantiles	Conditional exogenous treatment effects	Conditional endogenous treatment effects
$\tau = 0.1$	0.9011***	1.2750***
	(0.1106)	(0.3455)
$\tau = 0.25$	0.8068***	1.2397***
	(0.0781)	(0.1757)
$\tau = 0.5$	0.7140***	1.2408***
	(0.0576)	(0.1460)
$\tau = 0.75$	0.6425***	1.2342***
	(0.0617)	(0.2600)
$\tau = 0.9$	0.8015***	1.4157***
	(0.1060)	(0.4427)

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Analytical standard errors in parentheses, see details in Stata (Frölich and Melly, 2010).

TABLE 9 Unconditional quantile treatment effects of digital technology adoption.

Quantiles	Conditional exogenous treatment effects	Conditional endogenous treatment effects
$\tau = 0.1$	0.8997***	0.9054***
	(0.0006)	(0.0018)
$\tau = 0.25$	0.8078***	0.8127***
	(0.0094)	(0.0051)
$\tau = 0.5$	0.7191***	0.7260***
	(0.0030)	(0.0028)
$\tau = 0.75$	0.6450***	0.6604***
	(0.0047)	(0.0076)
$\tau = 0.9$	0.8351***	0.8145***
	(0.0061)	(0.0137)

***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Analytical standard errors in parentheses, see details in Stata (Frölich and Melly, 2010).

In the exogenous CQTE model, the income effect of digital technology adoption reaches its peak of 90.11% at the 0.1 quantile, gradually decreasing thereafter, reaching a minimum of 64.25% at the 0.75 quantile. It rebounds to 80.15% at the 0.9 quantile but remains lower than the 80.68% observed at the 0.25 quantile. In the CQTE model, with endogeneity considered, the income effect of digital technology adoption also exhibits a U-shaped trend. The effect reaches 127.5% at the 0.1 quantile, declines to a minimum of 123.42% at the 0.75 quantile, and rebounds at the 0.9 quantile. Overall, considering the results from both the exogenous and endogenous treatment effects models, digital technology adoption has a positive impact on household income across various income quantiles. Specifically, farm households situated at the lower tail (low income) and upper tail (high income) of the income distribution tend to benefit more from adopting digital technology.

Due to the heavy reliance of the CQTE model on individual-level characteristics when interpreting the estimated results, which may not be necessarily of concern to policymakers, we use the UQTE model for further estimation (see Table 9). Estimations from both the exogenous and endogenous UQTE models consistently indicate that digital technology adoption has a positive impact on rural household incomes across all quantiles. Furthermore, the impact exhibits a U-shaped trend, decreasing initially and then increasing as quantiles rise. Notably, the adoption has a more pronounced effect on lower quantiles ($\tau = 0.1$ and $\tau = 0.25$). In the exogenous UQTE model, the income effect of digital technology adoption peaks at 89.97% at the lowest 0.1 quantile, declines to a minimum of 64.5% at the 0.75 quantile, and rebounds to 83.51% at the highest 0.9 quantile. In the endogenous UQTE model, the income effect is highest at the 0.1 quantile (90.54%), significantly higher than the other quantiles. Similarly, the income effect is smallest at the 0.75 quantile and then rises at the 0.9 quantile. These results indicate that digital technology adoption has a stronger impact on income growth for both the lower-income and highest-income groups, consistent with conclusions from CQTE estimations. However, when some observed characteristics are relinquished, the UQTE estimation results demonstrate that the income-growth effect of digital technology adoption is significantly higher for the lowest-income group ($\tau = 0.1$) than for other income groups. Although there is a slight increase in the income effect at the 0.9 quantile, its value is comparable to that of the 0.25 quantile. This finding suggests that the adoption of digital technology has contributed to the movement of more farmers into the upper-middle-income group, thereby mitigating income disparities among farm households to some extent.

6 Conclusion and policy implications

This study examines the factors influencing the adoption of digital technology by rural households in China's ethnic minority regions and how this adoption affects their income levels and income distribution. The empirical analysis utilizes survey data from rural households in the Changji Hui Autonomous Prefecture of the Xinjiang Uygur Autonomous Region in China. The ESR model is employed to examine the impact of adoption on household income, taking into account potential selection bias caused by observable and unobservable factors. Subsequently, robustness tests are conducted using the MTEs and treatment effects models. Additionally, the QTE model is used to estimate the adoption effects at different income quantiles to assess the impact of adoption on income distribution.

This suggests that in the process of rural digitization, in order to guarantee that farmers of all ethnicities can benefit from the advantages of digital technology on an equal basis, measures need to be taken to alleviate the digital exclusion that may arise from ethnic differences, including language and culture. The research findings also highlight that the adoption of digital technology and its associated dimensions (including digital production, digital information processing, and digital marketing) has a positive impact on the income growth of rural households. This influence is primarily achieved by empowering agricultural production and operations and facilitating the transformation of household livelihood strategies. Additionally, adoption reduces the willingness of households to engage in land transfer. Specifically, digital technology adoption enables a reduction in the reliance of agricultural production on traditional labor inputs, not only allowing households to increase their agricultural income but also enhancing the potential for non-farm employment, thereby promoting diversified income growth. However, it is worth noting that the increase in non-farm income is relatively modest, and ethnic minority households face certain challenges in utilizing digital technology to improve non-farm income. Furthermore, the QTE results indicate that the income effects are higher for low-income households ($\tau = 0.10$, $\tau = 0.25$) compared to upper-middle-income households ($\tau = 0.50$, $\tau = 0.75$), thus helping to narrow income disparities within rural areas.

Based on these findings, this study yields some policy implications. First, in response to the barriers to digital technology adoption among ethnic minority farmers, such as Uighurs, it is recommended that the government and businesses collaborate to increase investment in multilingual interfaces and content localization. This would ensure that ethnic minority households can access and utilize digital resources without encountering obstacles.

Second, considering the differences among ethnic groups and income levels of households, differentiated digital technology promotion strategies need to be formulated and implemented. Specifically, specialized training and support services should be provided for minority ethnic farm households to help them overcome technological barriers and enhance their digital skills. For low-income households, more substantive support policies should be introduced, such as providing financial subsidies to alleviate their economic burden in adopting digital technology, thus ensuring their equal access to the development opportunities brought by digital technology. For upper-middle-income households, emphasis should be placed on technology upgrades and demonstration projects. Governments can encourage them to introduce advanced equipment through subsidies for equipment procurement and targeted technical guidance. Meanwhile, support them in co-establishing demonstration bases with research institutions and digital agriculture enterprises, and promote digital technology application experiences through open days, on-site visits, and online live broadcasts, thus leveraging the demonstration effects.

Third, efforts should be made to strengthen the non-farm employment and entrepreneurship support system. Specifically, for minority ethnic households, vocational guidance, skills training, and market information services should be provided to help them better integrate into non-farm employment markets or engage in self-employment. Additionally, it is crucial to actively encourage the deep integration and widespread application of digital platforms, such as e-commerce platforms and social media in rural areas of ethnic regions. This will enable households to have access to more diverse and convenient sales channels and entrepreneurial platforms, thereby further expanding their sources of income.

Although this study systematically analyzes the impact of digital technology adoption on rural household income in ethnic minority areas based on field survey data from Xinjiang, certain limitations remain. On the one hand, this study cannot capture the dynamic evolution process of the relationship between digital technology adoption and changes in household income. Future research endeavors could address this by establishing a tracking survey database to explore the persistent impact of digital technology adoption on household income. On the other hand, subsequent research may expand the sample size, extend the scope to other ethnic minority regions, and conduct multi-regional comparative analyses to more comprehensively validate the theoretical mechanisms and heterogeneous effects of digital technology adoption on rural household income.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for this study involving human participants in accordance with the local legislation and institutional requirements. All participants were fully informed of the study's purpose, voluntary nature, and confidentiality measures prior to participation, and gave their verbal informed consent to participate in this study. No personally identifiable information was collected during data collection, and all data were anonymized to ensure confidentiality.

Author contributions

YT: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. LT: Conceptualization, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by the National Social Science Fund of China (Grant No. 21BTJ037).

Acknowledgments

The authors gratefully acknowledge the support provided by the "Digital Empowerment of Xinjiang" social practice team from the School of Economics at Xiamen University (ranked among the top 100 investigative teams in the "2023 China Research" by Southern Wind Window) in the collection of data.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1595575/full#supplementary-material

References

Abadie, A., Angrist, J., and Imbens, G. (2002). Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica* 70, 91–117. doi: 10.1111/1468-0262.00270

Aker, J. C. (2010). Information from markets near and far: mobile phones and agricultural markets in Niger. *Am. Econ. J.-Appl. Econ.* 2, 46–59. doi: 10.1257/app.2.3.46

Aker, J. C., and Ksoll, C. (2016). Can mobile phones improve agricultural outcomes? Evidence from a randomized experiment in Niger. *Food Policy* 60, 44–51. doi: 10.1016/j.foodpol.2015.03.006

Benyam, A., Soma, T., and Fraser, E. (2021). Digital agricultural technologies for food loss and waste prevention and reduction: global trends, adoption opportunities and barriers. *J. Clean Prod.* 323:129099. doi: 10.1016/j.jclepro.2021.129099

Bowen, R., and Morris, W. (2019). The digital divide: implications for agribusiness and entrepreneurship. lessons from Wales. *J. Rural Stud.* 72, 75–84. doi: 10.1016/j.jrurstud.2019.10.031

Cai, Y., Qi. W., and Yi, F. (2022). Mobile Internet adoption and technology adoption extensity: evidence from litchi growers in southern China. *China Agric. Econ. Rev.* 14, 106–121. doi: 10.1108/CAER-11-2020-0260

Chang, H. H., and Just, D. R. (2009). Internet access and farm household income: empirical evidence using a semi-parametric assessment in Taiwan. *J. Agric. Econ.* 60, 348–366. doi: 10.1111/j.1477-9552.2008.00189.x

Cheng, C., Gao, Q., Ju, K., and Ma, Y. (2024). How digital skills affect farmers' agricultural entrepreneurship? An explanation from factor availability. *J. Innov. Knowl.* 9:100477. doi: 10.1016/j.jik.2024.100477

Cornelissen, T., Dustmann, C., Raute, A., and Schönberg, U. (2018). Who benefits from universal child care? Estimating marginal returns to early child care attendance. *J. Polit. Econ.* 126, 2356–2409. doi: 10.1086/699979

Deller, S., Kures, M., and Conroy, T. (2019). Rural entrepreneurship and migration. *J. Rural Stud.* 66, 30–42. doi: 10.1016/j.jrurstud.2019.01.026

Di Falco, S., Veronesi, M., and Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *Am. J. Agr. Econ.* 93, 829–846. doi: 10.1093/ajae/aar006

Doksum, K. A. (1974). Empirical probability plots and statistical inference for nonlinear models in the two-sample case. *Ann. Stat.* 2, 267–277. doi: 10.1214/aos/1176342662

Firpo, S. (2007). Efficient semiparametric estimation of quantile treatment effects. *Econometrica* 75, 259–276. doi: 10.1111/j.1468-0262.2007.00738.x

Firpo, S., Fortin, N. M., and Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica* 77, 953–973. doi: 10.3982/ECTA6822

Frölich, M., and Melly, B. (2010). Estimation of quantile treatment effects with Stata. *Stata J.* 10, 423–457. doi: 10.1177/1536867X1001000309

Frölich, M., and Melly, B. (2013). Unconditional quantile treatment effects under endogeneity. *J. Bus. Econ. Stat.* 31, 346–357. doi: 10.1080/07350015.2013.803869

Gao, Y., Zang, L., and Sun, J. (2018). Does computer penetration increase farmers' income? An empirical study from China. *Telecommun. Policy* 42, 345–360. doi: 10.1016/j.telpol.2018.03.002

Goldfarb, A., and Tucker, C. (2019). Digital economics. *J. Econ. Lit.* 57, 3–43. doi: 10.1257/jel.20171452

Heckman, J. J. (2010). Building bridges between structural and program evaluation approaches to evaluating policy. *J. Econ. Lit.* 48, 356–398. doi: 10.1257/jel.48.2.356

Heckman, J. J., and Vytlacil, E. J. (2005). Structural equations, treatment effects, and econometric policy evaluation. *Econometrica* 73, 669–738. doi: 10.1111/j.1468-0262.2005.00594.x

Hong, Y., and Chang, H. (2020). Does digitalization affect the objective and subjective wellbeing of forestry farm households? Empirical evidence in Fujian province of China. *Forest Policy Econ.* 118:102236. doi: 10.1016/j.forpol.2020.102236

Hou, J., Huo, X., and Yin, R. (2019). Does computer usage change farmers' production and consumption? Evidence from China. *China Agric. Econ. Rev.* 11, 387–410. doi: 10.1108/CAER-09-2016-0149

Hubler, M., and Hartje, R. (2016). Are smartphones smart for economic development? *Econ. Lett.* 141, 130–133. doi: 10.1016/j.econlet.2016.02.001

Khanal, A., Mishra, A., and Koirala, K. (2015). Access to the internet and financial performance of small business households. *Electron. Commer. Res.* 15, 159–175. doi: 10.1007/s10660-015-9178-3

Koenker, R., and Bassett, G. (1978). Regression quantiles. *Econometrica* 46, 33–50. doi: 10.2307/1913643

Kumar, A., Saroj, S., Joshi, P. K., and Takeshima, H. (2018). Does cooperative membership improve household welfare? Evidence from a panel data analysis of smallholder dairy farmers in Bihar, India. *Food Policy* 75, 24–36. doi: 10.1016/j.foodpol.2018.01.005

Lassalas, M., Duvaleix, S., and Latruffe, L. (2024). The technical and economic effects of biodiversity standards on wheat production. *Eur. Rev. Agric. Econ.* 51, 275–308. doi: 10.1093/erae/jbad044

Li, F., Zang, D., Chandio, A. A., Yang, D., and Jiang, Y. (2023). Farmers' adoption of digital technology and agricultural entrepreneurial willingness: evidence from China. *Technol. Soc.* 73:102253. doi: 10.1016/j.techsoc.2023.102253

Li, W. J., Menjivar, J. R., Zhang, L., and Zhang, J. B. (2021). Climate change perceptions and the adoption of low-carbon agricultural technologies: evidence from rice production systems in the Yangtze River Basin. *Sci. Total Environ.*759:143554. doi: 10.1016/j.scitotenv.2020.143554

Liu, M., Min, S., Ma, W. L., and Liu, T. J. (2021). The adoption and impact of E-commerce in rural China: application of an endogenous switching regression model. *J. Rural Stud.* 83, 106–116. doi: 10.1016/j.jrurstud.2021.02.021

Liu, Y., Chen, R., Chen, Y., Yu, T., and Fu, X. (2024). Impact of the degree of agricultural green production technology adoption on income: evidence from Sichuan citrus growers. *Hum. Soc. Sci. Commun.* 11:1160. doi: 10.1057/s41599-024-03693-z

Lokshin, M., and Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *Stata J.* 4, 282–289. doi: 10.1177/1536867X0400400306

Ma, W., Zhou, X., Boansi, D., Horlu, G. S. A., and Owusu, V. (2024). Adoption and intensity of agricultural mechanization and their impact on non-farm employment of rural women. *World Dev.* 173:106434. doi: 10.1016/j.worlddev.2023.106434

Ma, W. L., Abdulai, A., and Goetz, R. (2018). Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *Am. J. Agr. Econ.* 100, 502–520. doi: 10.1093/ajae/aax079

Maina, F., Mburu, J., and Nyang'anga, H. (2024). Drivers of extent of commercialization of potato farming through digital marketing platforms in Nakuru County, Kenya. *Front. Sustain. Food Syst.* 8:1307978. doi: 10.3389/fsufs.2024.1307978

Min, S., Min, L., and Huang, J. (2020). Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. *J. Asian Econ.* 70:101219. doi: 10.1016/j.asieco.2020.101219

Mondejar, M. E., Avtar, R., Diaz, H. L. B., Dubey, R. K., Esteban, J., Gomez-Morales, A., et al. (2021). Digitalization to achieve sustainable development goals: steps towards a smart green planet. *Sci. Total Environ.* 794:148539. doi: 10.1016/j.scitotenv.2021.148539

Muto, M., and Yamano, T. (2009). The impact of mobile phone coverage expansion on market participation: panel data evidence from Uganda. *World Dev.* 37, 1887–1896. doi: 10.1016/j.worlddev.2009.05.004

Nikam, V., Ashok, A., and Pal, S. (2022). Farmers' information needs, access and its impact: evidence from different cotton producing regions in the Maharashtra state of India. *Agric. Syst.* 196:103317. doi: 10.1016/j.agsy.2021.103317

Qiu, L., Zhong, S., and Sun, B. (2021). Blessing or curse? The effect of broadband Internet on China's inter-city income inequality. *Econ. Anal. Policy* 72, 626–650. doi: 10.1016/j.eap.2021.10.013

Rijswijk, K., Klerkx, L., Bacco, M., Bartolini, F., Bulten, E., Debruyne, L., et al. (2021). Digital transformation of agriculture and rural areas: a socio-cyber-physical system framework to support responsibilisation. *J. Rural Stud.* 85, 79–90. doi: 10.1016/j.jrurstud.2021.05.003

Shen, Z., Wang, S., Boussemart, J-. P., and Hao, Y. (2022). Digital transition and green growth in Chinese agriculture. *Technol. Forecast. Soc. Chang.* 181:121742. doi: 10.1016/j.techfore.2022.121742

Sparrow, R., and Howard, M. (2021). Robots in agriculture: prospects, impacts, ethics, and policy. *Precis. Agric.* 22, 818–833. doi: 10.1007/s11119-020-09757-9

Tadesse, G., and Bahiigwa, G. (2015). Mobile phones and farmers' marketing decisions in Ethiopia. *World Dev.* 68, 296–307. doi: 10.1016/j.worlddev.2014.12.010

Tchamyou, V. S., Erreygers, G., and Cassimon, D. (2019). Inequality, ICT and financial access in Africa. *Technol. Forecast. Soc. Chang.* 139, 169–184. doi: 10.1016/j.techfore.2018.11.004

Tsai, W. (2001). Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance. *Acad. Manage. J.* 44, 996–1004. doi: 10.2307/3069443

Weerakkody, V., Dwivedi, Y. K., El-Haddadeh, R., Almuwil, A., and Ghoneim, A. (2012). Conceptualizing e-inclusion in Europe: an explanatory study. *Inf. Syst. Manage.* 29, 305–320. doi: 10.1080/10580530.2012.716992

Wolfert, S., Ge, L., Verdouw, C., and Bogaardt, M-. J. (2017). Big data in smart farming—a review. *Agric. Syst.* 153, 69–80. doi: 10.1016/j.agsy.2017.01.023

World Bank (2016). *World Development Report 2016: Digital Dividends*. Washington, DC: World Bank.

World Bank (2017). *ICT in Agriculture (Updated Edition): Connecting Smallholders to Knowledge, Networks, and Institutions*. Washington, DC: World Bank.

World Bank (2019). *Future of Food: Harnessing Digital Technologies to Improve Food System Outcomes*. Washington, DC: World Bank.

Wu, Y., Duan, K., and Zhang, W. (2023). The impact of internet use on farmers' land transfer under the framework of transaction costs. *Land* 12:1855. doi: 10.3390/land12101855

Xia, H., Yu, H., Wang, S., and Yang, H. (2024). Digital economy and the urban–rural income gap: impact, mechanisms, and spatial heterogeneity. *J. Innov. Knowl.* 9:100505. doi: 10.1016/j.jik.2024.100505

Xie, H., Zhang, J., and Shao, J. (2023). Difference in the influence of internet use on the relative poverty among farmers with different income structures. *Econ. Anal. Policy* 78, 561–570. doi: 10.1016/j.eap.2023.03.022

Zhang, J., Mishra, A. K., and Zhu, P. (2019). Identifying livelihood strategies and transitions in rural China: is land holding an obstacle? *Land Use Pol.* 80, 107–117. doi: 10.1016/j.landusepol.2018.09.042

Zhang, Y., Long, H., Ma, L., Tu, S., Li, Y., Ge, D., et al. (2018). Analysis of rural economic restructuring driven by e-commerce based on the space of flows: the case of Xiaying village in central China. *J. Rural Stud.* 93, 196–209. doi: 10.1016/j.jrurstud.2018.12.001

Zheng, H., Ma, W., and Li, F. (2021). Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. *Food Policy* 102:102044. doi: 10.1016/j.foodpol.2021.102044

Zheng, Y. Y., Zhu, T. H., and Jia, W. (2022). Does Internet use promote the adoption of agricultural technology? Evidence from 1449 farm households in 14 Chinese provinces. *J. Integr. Agric.* 21, 282–292. doi: 10.1016/S2095-3119(21)63750-4

Zhou, F., and Deng, H. (2023). Creation or disruption? Doubts from the internet applications in China's rural sector. *J. Innov. Knowl.* 8:100450. doi: 10.1016/j.jik.2023.100450

Zhou, X., Cui, Y., and Zhang, S. (2020). Internet use and rural residents' income growth. *China Agr. Econ. Rev.* 12, 315–327. doi: 10.1108/CAER-06-2019-0094

Zhu, X., Hu, R., Zhang, C., and Shi, G. (2021). Does Internet use improve technical efficiency? Evidence from apple production in China. *Technol. Forecast. Soc. Chang.* 166:120662. doi: 10.1016/j.techfore.2021.120662