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Smartphone access, digital economy, and pesticide use intensity: Evidence from China

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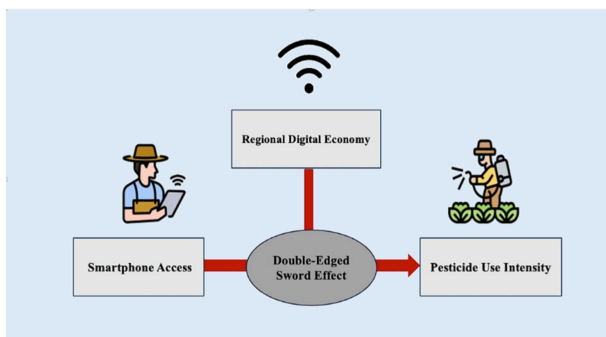
HIGHLIGHTS

- Smartphone access has a "double-edged sword" effect on pesticide use intensity.
- Greater access led to a higher pesticide use intensity in regions with low level of digital economy.
- Greater access led to a lower pesticide use intensity in regions with high level of digital economy.
- A comprehensive social and engineering integration is needed to reduce pesticide use intensity.

GRAPHICAL ABSTRACT



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ABSTRACT

Pesticide overuse has been an increasing concern in China. Digital technology, such as smartphone access, is considered an effective way to promote proper use of pesticides. Using the Chinese Extended Family Database (2015, 2017, and 2019), this study empirically examines the impact of smartphone access on pesticide use intensity among Chinese farmers. The results show a "double-edged sword" effect of smartphone access on pesticide use intensity. In rural areas with a low level of digital economy, greater smartphone access led to higher pesticide use intensity. In rural areas with a high digital economy level, smartphone access reduced pesticide use intensity. The study results show that reducing pesticide use intensity through digital technology is not a linear process but a complicated one that involves social and engineering integration, including an increase in access to smartphones, development of a regional digital economy, reconstruction of agricultural extension systems, and enhancement of the capacity of digital technology.

1. Introduction

Proper pesticide use is a challenging issue for many developing countries that attempt to modernize their agricultural economy (Enserink et al., 2013; Popp et al., 2013; Verger and Boobis, 2013; Wu et al., 2018; Xie et al., 2020; Zhang et al., 2015a). Pesticide overuse is

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widely observed in those countries, such as China (Zhang et al., 2015a, 2015b), Thailand (Grovermann et al., 2013), Kuwait (Jallow et al., 2017), and Vietnam (Normile, 2013; Salazar and Rand, 2020). Pesticide overuse leads to environmental pollution (Hao and Yang, 2013), causes food safety concerns (Zhang et al., 2021), and increases human health risks (Enserink et al., 2013; Zhang et al., 2018; Möhring et al., 2020). Therefore, many technical supports and regulatory strategies have been introduced to reduce pesticide use intensity and promote the proper use of pesticides (Enserink et al., 2013; Normile, 2013; Möhring et al., 2020).

Digital technologies have been applied to transform agricultural systems and offer an opportunity for properly using pesticides in many developing countries. Digital agriculture integrating digital technology with agricultural production helps improve agricultural resource use efficiency and sustainability (Rotz et al., 2019; Clapp and Ruder, 2020). Digital technologies are integrated with automation technologies such as intelligent tractors, drones, and robots to implement variable rate applications that precisely deliver seeds, water, fertilizers, and pesticides and, therefore, significantly reduce the environmental impacts of agricultural production (Clapp and Ruder, 2020). Digital technologies also reduce the cost of tracking product origins, increase transparency, improve public trust on the value chain of agricultural products, and help promote environment-friendly production behaviors (Fabregas et al., 2019). Through mining big data on the Internet, digital technologies improve farmers' communication, learning, and information sharing (Nyamba and Mlozi, 2012; Baumüller, 2018; Zhong et al., 2023). In China, businesses, such as pesticide producers Bayer and Sinochem and drone manufacturers XAG technology and DJ-Innovations, are actively building online platforms to support farmers adopting new pesticide use technologies.

As a digital technology, mobile phones play a key role in the digital transformation of agriculture (Min et al., 2020). Mobile phone technology has become increasingly adopted to promote agricultural extension services in developing countries (Aker, 2011; Birke et al., 2019; Cole and Fernando, 2021; Folitse et al., 2019; Janc et al., 2019). Mobile phones help disseminate product information and increase the adoption of the recommended agrochemical application rate by 22 % in sub-Saharan Africa and India (Fabregas et al., 2019). Mobile phones also connected the ICT revolution to the smallholder cotton farmers and helped increased the adoption of pesticide use recommendations and biological pest control methods through an innovative voice-based ICT advisory service in India (Cole and Fernando, 2021). In Uganda, where resources are scarce, mobile phones help farmers to access information on agricultural inputs including pesticides and increase the likelihood of using these inputs (Freeman and Qin, 2020). In Rwanda and Uganda, mass social media campaigns involving the use of mobile phones effectively improved farmers' awareness of pesticide risks and safety measures and boosted the adoption of environmentally safer alternatives to synthetic pesticides (Tambo et al., 2023). In Ecuador, mobile phone applications helped increase the adoption of low-toxicity pesticide products among the blackberry farmers (Carrión-Yaguana et al., 2020).

The impact of mobile phones on farmers' behaviors in agricultural input use is not uniform and has been highly affected by the development of the technology itself. Early mobile technology relied on text messages in the 2G era and pictures, graphics, voice messages in the 3G era. These traditional mobile technologies were not able to provide sophisticated advice on agricultural practices or new technologies in many developing countries (Awuor and Otanga, 2019; Nakasone et al., 2014). The primary reason is that reading and interacting with text messages through mobile phones requires a high level of literacy that smallholder farmers do not have (Nakasone et al., 2014; Wyche and Steinfield, 2015), and eventually leads to the problem of information overload (Awuor and Otanga, 2019).

However, smartphone technology with video message functions in the 4G and 5G eras allows farmers with a limited literacy to obtain agricultural knowledge and information easily. Video information through smartphones helps farmers understand the advantages and disadvantages of new farm technologies, ensuring accurate application (Zheng and Ma, 2023). Empirical research shows that easily accessible videos through smartphones can deliver complex and rich knowledge and information on pesticides, increase farmers' understanding of pesticides, and help farmers make more informed decisions on pesticide use (Chowdhury et al., 2015). Many social media platforms allow some experienced farmers to be video content creators and become locally influential experts (Šūmane et al., 2018). Learning through videos allows farmers to integrate such information with their local experiences to update their knowledge and innovate their farming practices (Zossou et al., 2009).

Although mobile phone technology, especially access to smartphones, helps farmers increase their knowledge of pesticides and thus potentially reduce pesticide use, farmers in many developing countries still tend to apply more pesticides due to agricultural productivity concerns (Grovermann et al., 2013; Jallow et al., 2017; Salazar and Rand, 2020; Schreinemachers et al., 2020; Xie et al., 2020; Zhang et al., 2015b, 2015a). Pesticide overuse was especially apparent in China, where the public agricultural extension system collapsed in 1980s (Zhang et al., 2015a). Without public agricultural extension services, pesticide sellers have become the primary source of information and knowledge on pesticides to farmers in China (Fan et al., 2015; Jin et al., 2015). The profit motive often prompts sellers to oversell agricultural supplies through various tactics. Since farmers in China are generally less educated and poorly trained, frequent updates on pesticide varieties and even changes in packaging further exacerbate such information asymmetry between farmers and pesticide sellers (Jin et al., 2015). Motivated by profits, pesticide sellers often promote pesticide sales by overemphasizing the role of pesticides in agricultural production, resulting in excessive purchase and overuse of pesticides in China (Wang and Gu, 2013). Although mobile phones help farmers obtain market information about pesticides (Cole and Fernando, 2021; Freeman and Qin, 2020; Tambo et al., 2023), the same technology can also be used by pesticide sellers to directly market their products to farmers, which leads to pesticides overuse. A survey from farmers in China suggested that mobile phone technology, especially smartphone access, has a double-edged sword effect on pesticide use: smartphone access resulted in a 33 % increase in pesticide expenditure among the farmers in the lowest 20th quantile of the pesticide expenditure, and a 36–39 % reduction in pesticide expenditure among the farmers in the upper 60th and 80th quantiles of pesticide expenditure (Ma and Zheng, 2022).

However, no study has yet attempted to systematically analyze the inherent cause of such a double-edged sword effect of mobile phone technology on pesticide use. This study aims to understand the underlying impact of smartphone access on pesticide use in China. The hypothesis is that the development of a regional digital economy where mobile phones operate significantly impacts how smartphone access affects pesticide use. Digital learning through smartphones relies on the smooth operation of a local digital network characterized by an excellent digital infrastructure, a large population of internet users, and active content creation. For example, the expansion of regional mobile phone coverage induces farmers' market participation (Muto and Yamano, 2009) and increases the provision of agricultural extension services (Aker, 2011). Without the support of a well-developed local digital network, smartphones are no better than traditional feature phones, and therefore, farmers with smartphones cannot reap the benefits of digital learning. For example, in extremely remote rural communities in Papua, Indonesia, smartphones were mainly used for calls and text messages (Heimerl et al., 2015).

Based on longitudinal survey data on rural households in China, this study assesses how smartphone access and the development of the regional digital economy jointly affect farmers' decisions on pesticide use, which explains the double-edged sword effect of smartphone access on pesticide use among Chinese farmers. As a developing country where smartphones are widely used, China provides an interesting example to understand the impacts of smartphones and mobile technology on pesticide use in agriculture. Like many other developing countries in South Asia and Africa, agriculture in China is still dominated by smallholder farmers. Therefore, the findings on the impact of smartphones on pesticide use in China can help developing countries to develop effective policies and strategies to properly use pesticides and other agrochemicals.

2. Research background

2.1. Pesticide overuse in China

In traditional agriculture in China, farmers rely on intensive cultivation techniques such as timely planting and harvesting, weeding, and deep plowing to physically prevent and control plant diseases and pests (Wen, 2016). Despite the fast growth of the "green revolution" in Western developed countries and other parts of the world, China limited manufacturing capacity and use of synthetic fertilizers and pesticides until the 1980s (Pan et al., 2020). Agrochemicals, including fertilizers and pesticides, grew in popularity in the middle of the 1980s for two reasons. First, China began to implement its "open door" policies to foreign technology and investment, significantly increasing the capacity of manufacturing and supplying agrochemicals in China. Second, China widely implemented the Rural Household Contract System to grant farmers nearly complete freedom to conduct their agricultural operations, which gave farmers the freedom to use agrochemicals to increase crop yields and farm income.

Fig. 1a presents the total amount of pesticide usage (the left axis) and the pesticide use intensity on the sown area of crops in China from 1991 to 2021. The total pesticide use in China increased from 0.77 million tons in 1991 to 1.32 million tons in 1999, a nearly 73 % increase. The total pesticide usage dropped slightly in 2000, and resumed steady growth in 2001, reaching its peak of 1.81 million tons in 2013. The intensity of pesticide use in China experienced similar changes over that period and reached its peak level of 11.14 kg/ha in 2013. The fast growth in pesticide use has become a significant concern in China. The Chinese government began to take a series of actions to reduce pesticide use in 2010. The Chinese Ministry of Agriculture issued the Action Plan on Agricultural Crop Pest Control and Disease Prevention in 2010 to prevent crop diseases and control crop damage while reducing pesticide use and enhancing agricultural product safety. The Central Government in China subsequently issued its pesticide reduction policy in the 14th Five-Year Plan for National Economic and Social Development of the People's Republic of China and the Outlook of the 2035 Long-term Development Goals. These policy changes on pesticide use and their implementation had impacts. As shown in Fig. 1a, both the total pesticide usage and the intensity of pesticide use declined steadily after 2013, and lowered to 1.24 million tons and 7.35 kg/ha, respectively, in 2021.

Fig. 1b compares the intensity of pesticide use measured by the ratio of the average weight of active ingredients per unit of farmland in kg/ha in China to the world from 1990 to 2021, based on data from FAO.[1] From 1990 to 1992, the intensity of pesticide use in China was lower than the world average, as the ratio was less than one. However, from 1993 to 2018, the intensity of pesticide use in China increased significantly and surpassed the world average level. The peak was in 2009 when the intensity of pesticide use in China was approximately 1.36 times the world average. The intensity of pesticide use in China started to drop below the world average in 2019.

2.2. The growth of mobile communication in China

China launched its first commercial service of the first-generation analog mobile communication system (1G) in 1987. Over the next 35 years, China has steadily upgraded its mobile communication system from 1G to 5G and currently owns the largest 5G network in the world. According to the China Ministry of Industry and Information Technology, China had 475 million 5G mobile phone users, which accounted for >70 % of the global 5G network users by July 2022. China operates 1.97 million 5G base stations, accounting for over 60 % of the active 5G base stations worldwide. The growth of mobile communication in the past 35 years in China is further evidenced by a sharp rise in mobile phone penetration rate, a swift conversion to smartphones, and a steady increase in mobile internet speed.

Fig. 2a shows the penetration rates, i. e., the number of phones per 100 people, of hardline phones and mobile phones in China from 2000 to 2021. Over the 20 years, the mobile phone penetration rate had risen from 6.7 to 116.3, while the penetration rate for the hardline phones increased from 12.4 in 2000 to 28.1 in 2006 and then decreased to 12.8 in 2021. By the end of 2021, there were 1.82 billion telephone users in China, including 1.64 billion mobile phone users and only 181 million hardline phone users.

Fig. 2b shows the growth of smartphones with 3G/4G services in China from 2010 to 2018 in terms of the number of phone users, the ratio of the smartphone users among all mobile phone users, and the ratio of the number of 3G/4G base stations among all mobile base stations. The number of 3G/4G users was only 47.05 million, accounting for 5.5 % of the total mobile phone users in 2010. It grew to 1.3 billion in 2018, i. e., 83.4 % of mobile phone users. The number of 3G/4G base stations accounted for 32.8 % of all base stations in 2010 and had grown to 75.5 % by 2018.

As a result, the number of mobile internet users has also grown rapidly in China. According to the China Internet Network Information Center, the number of mobile internet users in China grew from 50.4 million in 2007 to 1.03 billion in 2021, corresponding to 24 % of the total internet users in 2007 and 99.7 % in 2021. In other words, smartphones have become essential for people in China who want to access the Internet.

The speed of downloading and uploading mobile Internet has also increased rapidly. Fig. 2c presents the average downloading speed of the 4G network from 2016 Q3 to 2021 Q4. Mobile internet speed has skyrocketed since the launch of the 5G network in China. According to the China Information and Communication Academy, the average downloading speed for 5G users in China was 341.2 Mbps, and the average uploading speed was 71.98 Mbps in 2022, among the world's fastest mobile networks. Mobile smartphones are predominantly used for instant messaging, video sharing, and watching short movies.

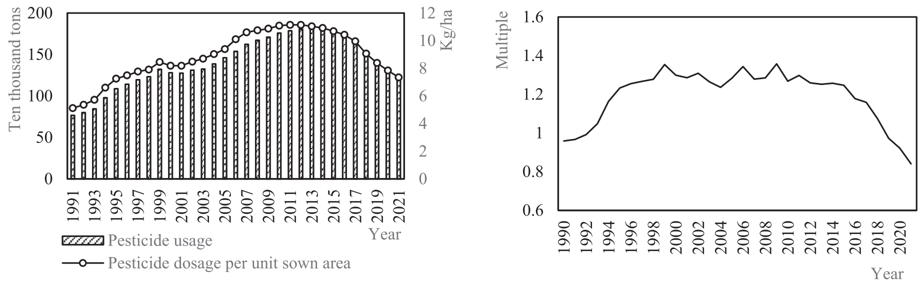
Despite the staggering growth of mobile communication in China, China's rural regions are lagging. According to the China Internet Network Information Center, the internet penetration rate was 58.8 % in the rural regions and 82.9 % in urban and urbanizing regions in China in 2022. The internet speed in rural regions is far slower than in urban and urbanized regions.

3. Method

3.1. Data

This research uses the longitudinal survey data from the Chinese Family Database (CFD) at Zhejiang University and the China Household Finance Survey (CHFS) conducted by the Survey and Research Center for China Household Finance at China Southwestern University of Finance and Economics (SWUFE). The CFD survey adopted a three-stratified probability proportion to size (PPS) sampling approach to select its household samples for the longitudinal survey (Wu et al., 2018). The selected samples include households from 29 provinces,

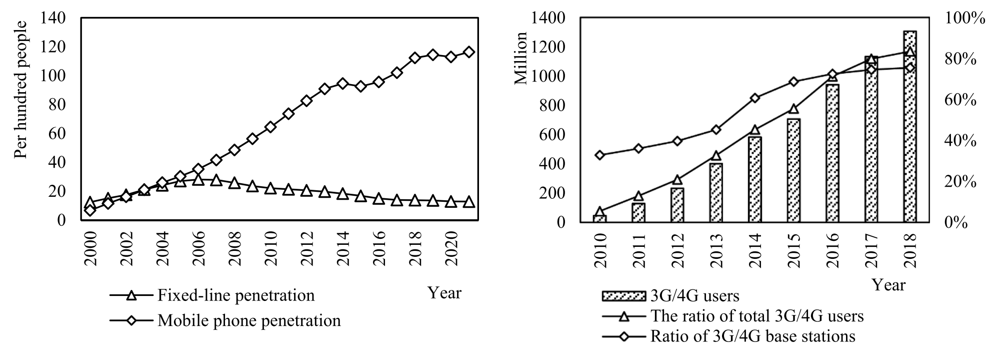
[1] Source: FAO. Pesticides Use. FAOSTAT, URL. https://www.fao.org/faostat/zh/#data/RP



(a) Pesticide usage and use intensity in China (1991-2021)

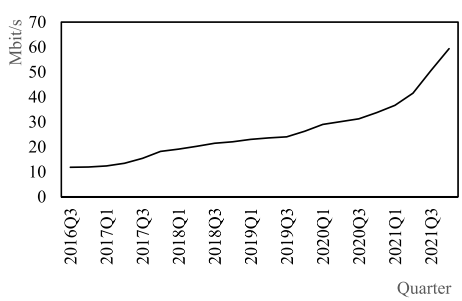
(b) Ratio of pesticide use intensity between China and the World (1990-2021)

Fig. 1. Pesticide use intensity comparisons in China and the World.



(a) Penetration Rate of Hardline and Mobile Phones in China (2000-2021)[1]

(b) Development of China's smart Phones (3G/4G) (2010-2018)[2]



(c) Average Download Rate of 4G networks in China (2013- 2021)[3]

Fig. 2. The mobile communication infrastructure growth patterns in China.

autonomous regions, and metropolitan areas directly under the control of the central government in China. Through scientific sampling, modern survey techniques, and rigorous survey management, the longitudinal surveys aim to collect high-quality micro information on Chinese families to conduct in-depth research on various issues related to Chinese families. Among them, the 2015 data involved a rural sample of 22,535 households; The 2017 data involved a rural sample of 24,764 households; The 2019 data involved a rural sample of 21,815 households. This study extracted all rural household samples growing staple food and/or cash crops from the CFD database, which included 5054 in 2015, 9142 in 2017, and 8757 in 2019. We use these three rounds of survey data to form a non-equilibrium panel data. The CFD survey contains the essential information on farmers' farming operations, including pesticide use and the information on mobile phones, the Internet, and other digital technologies, and is used in this study.

3.2. Variables

3.2.1. Dependent variable

This study uses pesticide use intensity as the dependent variable. The quantity and expenditure of pesticides applied per unit area can be used to define pesticide use intensity, but the CFD survey only reported the quantity of pesticide applied in 2015, and not in other years. Therefore, we define the pesticide use intensity as the ratio of the total pesticide expenditure to the sown area following other similar studies (Zhu and Wang, 2021). This study takes the logarithmic value of the average pesticide expenditure to reduce the impacts of those extreme values on the results.

3.2.2. Variables of interest

This study includes two independent variables as the variables of interest. The first is access to the smartphone. Farmers in China mainly access digital technology services through mobile Internet and smartphones. The CFD contains specific questions on the use of mobile phones among farmers, including the specific types of mobile phones being used. Following the similar studies (Khan et al., 2022; Ma and Zheng, 2022), this study uses a dummy variable to indicate farmers' smartphone access: one if using a smartphone and zero otherwise. The second is the digital economy index (DEI), which measures regional differences in the development in digital economy in China. DEI is derived from five indicators: internet penetration rate, internet-related employment, internet-related economic output, mobile internet users, and digital inclusive finance index. China National Bureau of Statistics compiles the first four indicators, and the last one is jointly compiled by the Digital Finance Research Center of Peking University and the Ant Financial Services Group. The five indicators were further standardized and aggregated to calculate the composite DEI of all 30 provinces, autonomous regions, and metropolitans under the control of the Central Government following Zhao et al. (2020).

3.2.3. Control variables

The control variables include the characteristics of rural households, villages, and farmland that potentially affect farmers' decisions on pesticide use. The control variables on the rural household include farmers' age (Al Zadjali et al., 2014; Huang et al., 2020; Zhou and Jin, 2009), gender (Atreya, 2007; Wang et al., 2017), education (Al Zadjali et al., 2014; Goodhue et al., 2010; Jallow et al., 2017; Zhou and Jin, 2009), agricultural employment ratio (Hedlund et al., 2020), whether the household has any agricultural loan (Rahman, 2003), and received any agricultural guidance (Huang et al., 2021), and production for self-consumption (Sharifzadeh et al., 2019). The control variables for the village include per-capita income (Li et al., 2023)[2] and the distance of the village to the nearest market (Huang et al., 2020). The control variables on farmlands include the total sown area (Wu et al., 2018), planting structure (the ratio of the sown area for food crops) (Rahman, 2016), and land ownership (farmland certification) (Migheli, 2017). The study also contains the control variables on the household and year fixed effect being surveyed using dummy variables.

Table 1 presents detailed information on those variables, including the variable type, variable name, relevant survey questions, and calculating specifications and relevant references for using the variables.

3.3. Fixed effect models

Following Greene (2003) and Wooldridge (2010), this study applies a two-way fixed effect model to assess the effect of smartphone access on pesticide use intensity in China. The two-way fixed effect model was used in other studies using the same database being used in this study (Fan et al., 2023; Zheng et al., 2023a, 2023b; Zhu and Wang, 2021). Model 1, specified as Eq. (1), considers only the impact of smartphone access on pesticide use intensity:

[2] The existing literature mainly discussed the relationship between household income level and pesticide application. However, given the endogeneity of household income, we controlled the village's annual per capita income as an alternative. This variable is a higher-level variable that helps reduce the endogeneity.

Table 1
Description of variable indicators.

Variable category and name		Questions in the CFD Surveys	Variable specification	References
Dependent variable	Pesticide use intensity	How much did your family spend on pesticides (yuan)? What is your family's sown area for staple food and cash crops?	Ln (pesticide expenditure / the sown area + 1)	(Ma and Zheng, 2022; Wu et al., 2018)
Independent variable	Smartphone	What kind of mobile phone are you using now? (1. Smartphone; 2. Non-smartphone; 3. No cell phone)	One if "1" is selected, and zero otherwise	(Khan et al., 2022; Ma and Zheng, 2022)
	Digital economy index	As described in the text	In the range between 0 and 1	(Zhao et al., 2020)
Control variable	Age	The year of birth of the farmers interviewed	The year in which the survey was conducted minus the year of birth of the farmer interviewed	(L. Fan et al., 2015; Pan et al., 2021; Zheng et al., 2021; Zhou and Jin, 2009)
	Education	What is the literacy level of the farmers interviewed?? 1. Never went to school; 2. Primary school; 3. Junior high school; 4. High school; 5. Technical secondary school; 6. Junior college; 7. Bachelors; 8. Masters; 9. Ph. D. s	The actual years of education for options 1–9 are assigned 0, 6, 9, 12, 9, 12, 16, 19, and 23	
	Gender	The gender of the farmers interviewed	Select one for female, zero otherwise	
	Ratio of agricultural employment	How many members of your family are engaged in agricultural production and operation?	The number of farm laborers/ the workforce size	
	Ratio of staple food crops	What are the sown areas for staple food crops?	The sown area for staple food crops/ the total sown area of crops	
	Agricultural loan	Does your family have outstanding bank loans for agricultural operations? (1. Yes; 2. No)	One if "1" is selected, zero otherwise	
	Farmland Certification	Does your farmland have a rural land contract right certificate?	One if "1" is selected, zero otherwise	

(continued on next page)

Table 1 (*continued*)

Variable category and name		Questions in the CFD Surveys	Variable specification	References
	Production for self-consumption	What were the main uses of the agricultural products your family produced last year? 1. Direct sales; 2. Processed and sold; 3. For your use; 4. For your agricultural production; 5. Not yet produced; 6. To be sold; 7. Other.	One if "3", "4" is selected, zero otherwise	
	Agricultural guidance	Has your family received any technical guidance on agricultural production? (1. Yes; 2. No)	One if "1" is selected, zero otherwise	
	Total sown area	What is the sown area for both staple food crops and cash crops?	Ln (The total sown area + 1)	
	Annual per capita income of the village	What is the per capita disposable annual income of the residents in this community?	ln (Per capita income of the village +1)	
	Distance from market	What is the distance from the village to the nearest farmers' market or free market?	Ln (Distance from market +1), if the farmers' market or free market is in the village, the distance is 0	
	Household	Household who was interviewed	Dummy variable	–
	Year	The year when the survey was conducted	Dummy variable	

$$y_{it} = \alpha + \beta_1 x1_{it} + \gamma Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{1}$$

where i is the index for the farmers being surveyed, t indicates the year when the survey was conducted, y_{it} is the pesticide use intensity for farmer i in year t, $x1_{it}$ indicates whether farmer i uses a smartphone in year t, Z_{it} is a vector of all control variables for farmer i in year t, α is the intercept, β_1 is the regression coefficient for the independent variable $x1_{it}$, and γ is a vector of coefficients for the control variable vector Z_{it}, and μ_i is the household fixed effect, and ν_t is the time-fixed effect and ϵ_{it} is the residual term. The coefficient β_1 Eq. (1) indicates whether farmers' smartphone access impacts pesticide use intensity.

As discussed previously, smartphones rely on the availability and efficiency of the digital network to have the expected impacts on farmers' behavior change on pesticide application. We also introduce the DEI as an independent variable in the analysis to assess such effects. Model 2 considers the impacts of DEI by directly adding the DEI as an independent variable as specified in Eq. (2):

$$y_{it} = \alpha + \beta_1 x1_{it} + \beta_2 x2_{it} + \gamma Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

where $x2_{it}$ is the provincial DEI where farmer i is located in year t, β_2 is the regression coefficient for independent variable $x2_{it}$ and indicates if the regional development of the digital economy impacts the pesticide use intensity. Other variables are previously defined.

Model 3 considers the compounding impacts of both independent variables by adding an interaction of the two independent variables to Model (2) and is specified as follows in Eq. (3):

$$y_{it} = \alpha + \beta_1 x1_{it} + \beta_2 x2_{it} + \beta_3 x1_{it} x2_{it} + \gamma Z_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

where β_3 is the regression coefficient for the newly created interaction term $x1_{it}\ x2_{it}$ and indicates the compounding impacts of smartphone access and the regional development of the digital economy on the pesticide use intensity, and other variables are previously defined.

3.4. Endogeneity test

The fixed effects model is subject to some endogeneity concerns because of the potential reverse causal relationship between smartphone access and pesticide use intensity and potential omission of other critical control factors in our model specification. We tried to address potential endogeneity concerns by incorporating an instrumental variable in our models. Following Evans et al. (1992), we introduced an instrumental variables at a higher aggregate level to our models to address the endogeneity concerns. We select the smartphone usage rate in the village level as the instrumental variable for smartphone usage. This usage rate is the result of excluding the sample itself. The smartphone rate in the area reflects the prevalence of digital technology applications. Under the influence of neighborhood effects, individuals in the areas with higher smartphone rates are more likely to access smartphones, thereby meeting the requirement of instrumental variable relevance. However, the smartphone usage rate in a village does not affect individual decision on pesticide use, satisfying the requirement of instrumental variable exogeneity.

4. Results

4.1. Descriptive statistics of all variables

In this study, we restricted the age of the surveyed farmers to 16 to 80 years, as farmers who were too young or too old could not make their own decisions. To reduce measurement error, following Wu et al. (2018), we excluded households spending less than one yuan (RMB) on pesticide inputs per mu of sown area in any given year and/or did not report any sown area. Table 2 shows the descriptive statistics of all variables used in the study based on the combined rural household samples in 2015, 2017, and 2019. The household expenditure on pesticide use per hectare of sow area in a year ranges from ￥15 to ￥28,350. On average, a rural household uses ￥1440.17 per hectare of the sown area. The average smartphone value was 0.4071, indicating that 40.71 % of rural households use smartphones. The average digital Economy index is 0.3421 on a scale of 0 to 1.

The use of mobile phones, especially smartphones, among the selected rural households steadily increased over the sampling period. Among all selected rural households in this study, only a small percentage didn't have mobile phones, i.e., 3.8 % in 2015, 3.4 % in 2017, and 2.4 % in 2019, and the number gradually declined over the sampling periods. Among the selected rural households, 70 % used non-smartphones, and only 26.2 % used smartphones in 2015. The construction of 4G network base stations and the introduction and growth of 4G smartphones accelerate the adoption among rural households after 2015. The percentage of selected rural households using smartphones increased to 44 % in 2017 and 57.6 % in 2019, while the percentage using non-smartphones was decreased to 52.5 % in 2017 and 40 % in 2019.

Table 2
Statistical description and analysis results of each variable.

Variables	Sample size	Mean	SD.	Min	Max
Pesticide use intensity (Yuan·ha^{-1})	10,255	1440.17	2667.85	15	28,350
Pesticide use intensity (Yuan·ha^{-1}, logarithm)	10,255	6.4600	1.2291	2.7726	10.2524
Smartphone	10,343	0.4071	0.4913	0	1
Digital economy index	10,343	0.3421	0.0834	0.2332	0.7727
Age	10,343	54.3781	11.3548	16	80
Education	10,338	8.3405	4.5862	0	19
Gender	10,343	0.6365	0.4810	0	1
Ratio of agricultural employment	10,343	0.6133	0.3428	0	1
Ratio of staple food crops	10,343	0.9253	0.1865	0	1
Agricultural loan	10,327	0.0620	0.2411	0	1
Farmland certification	10,343	0.6462	0.4782	0	1
Production for self-consumption	10,301	0.4615	0.4985	0	1
Agricultural guidance	10,337	0.0928	0.2901	0	1
Total sown area (ha)	10,274	0.7363	1.0735	0.0007	10.6667
Total sown area (ha, logarithm)	10,274	0.4532	0.3892	0.0007	2.4567
Annual per capita income of the village (Yuan)	10,160	9,815.179	8,751.374	0	60,000
Annual per capita income of the village (Yuan, logarithm)	10,160	8.8151	0.9876	0	11.0021
Distance from market (km)	9,065	4.9320	6.0219	0	60
Distance from market (km, logarithm)	9,065	1.4300	0.8289	0	4.1109
IV	10,213	0.4062	0.2520	0	1

Note: The raw value minus the sample mean was used for regression analyses to avoid multicollinearity problems following Balli and Sørensen (2013). The sample size is obtained after excluding observations with missing values.

4.2. Fixed effect modeling results

We further excluded the top 0.1 %, 0.5 %, 1 % or 5 % of households in pesticide use intensity and total sown area to eliminate the potential impacts of sampling outliers to run the fixed effect models. The results are consistent. Table 3 presents the modeling results for the fixed effect models excluding the top 1 % of households in pesticide use intensity and total sown area while the supplemental materials presents the results excluding the top 0.1 %, 0.5 % and 5 % of households in pesticide use intensity and total sown area. Based on Model 1, the coefficient for the independent variable smartphones is 0.077 and statistically significant at a 90 % confidence level. This result indicates that smartphone access would increase pesticide use intensity. Following the calculation methods in Kennedy (1981), the estimated coefficient of 0.077 indicates that the average expenditure on pesticide use per ha is 7.9 %[3] higher for rural households using smartphones than those not using smartphones, including non-smartphones and not having phones. The modeling results from Model 2 confirm the findings from Model 1 on the significant and positive impacts of smartphone access on pesticide use intensity. The results from Model 2 also indicate that the reverse relationship between the digital economy index and the pesticide use intensity as the model coefficient for DEI is negative at a 95 % confidence level.

As shown in the modeling results from Model 3, the coefficients for smartphone and DEI have the same signs as those from Models 1 and 2, but they are no longer statistically significant. However, the coefficient for the cross-multiplication term between smartphone and DEI, which indicates the compounding impacts of smartphone access and the development of the digital economy, is negative and statistically significant at a 99 % confidence level. In other words, smartphone access with a growing digital economy could lead to a decline in the intensity of pesticide use.

Table 3 also shows the consistent impacts of all control variables across the three models. A higher ratio of agricultural employment and a larger scale of sown areas dedicated to staple food crops lead to higher pesticide use intensity, as indicated by their positive and statistically significant coefficients. The statistically positive coefficients indicate that carrying agricultural loans prompts farmers to increase pesticide use intensity. However, farmers who consume their own products tend

Table 3
The fixed effect modeling results excluding the top 1 % of households in pesticide use intensity, total sown area, and agricultural income per capita.

Variables	Model 1	Model 2	Model 3
Smartphone	0.0770*	0.0787*	−0.0085
	(0.0412)	(0.0412)	(0.0518)
Digital economy index (DEI)		−3.4017**	−1.2794
		(1.6443)	(1.8442)
Smartphone * DEI			−3.1269***
			(1.0853)
Age	0.0000	−0.0002	−0.0003
	(0.0030)	(0.0030)	(0.0030)
Education	−0.0006	−0.0006	−0.0004
	(0.0046)	(0.0046)	(0.0046)
Gender	0.0184	0.0188	0.0141
	(0.0519)	(0.0519)	(0.0519)
Ratio of agricultural employment	0.0494	0.0581	0.0577
	(0.0571)	(0.0571)	(0.0568)
Ratio of staple food crops	0.4386***	0.4328***	0.4379***
	(0.1120)	(0.1114)	(0.1111)
Agricultural loan	0.0731	0.0696	0.0661
	(0.0795)	(0.0795)	(0.0795)
Production for self-consumption	−0.0646	−0.0673*	−0.0711*
	(0.0400)	(0.0399)	(0.0400)
Farmland certification	−0.0507	−0.0532	−0.0572
	(0.0383)	(0.0384)	(0.0381)
Agricultural guidance	0.0269	0.0271	0.0235
	(0.0554)	(0.0554)	(0.0551)
Total sown area	−1.5150***	−1.5125***	−1.5118***
	(0.1001)	(0.1000)	(0.1000)
	−0.0277	−0.0278	−0.0285
	(0.0187)	(0.0187)	(0.0186)
Distance from market	−0.0274	−0.0252	−0.0266
	(0.0195)	(0.0197)	(0.0196)
Constant	7.1688***	7.1011***	7.1705***
	(0.2711)	(0.2726)	(0.2741)
Household fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
N	7998	7998	7998
Adjusted R^2	0.1787	0.1800	0.1824
F	25.5976	24.3475	23.2594

Note: Significance levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. The sample size is obtained after excluding observations with missing values.

[3] The calculation formula is: $g^* = exp\left(\widehat{c} - \frac{1}{2}\widehat{V}(\widehat{c})\right) - 1$.where g^* is the relative effect on pesticide use intensity of the presence of the factor represented by the smartphones, $\widehat{c}$ is the estimate of the regression coefficient, and $\widehat{V}(\widehat{c})$ is the variance of $\widehat{c}$.

to lower pesticide use intensity, as shown by significantly negative coefficients at the 99 % confidence level. A larger scale of operation indicated by the total sown area leads to lower pesticide use intensity, as indicated by negative and statistically significant coefficients. The coefficients for other control variables, including farmers' age, gender, years of education, farmland certification, the annual per capita income of the village, and distance from the market, don't significantly impact pesticide use intensity as their coefficients are not statistically significant.

Based on the fixed effect results in Model 3, we also plot the interactive impacts of smartphone access and the DEI on pesticide use intensity in Fig. 3, where the x-axis represents smartphone access and the y-axis represents the pesticide use intensity. Following Li and Sun (2017), these impacts were evaluated at the sample means of all control variables, and the high and low digital economy development levels were defined as the top and bottom 10 % DEI levels of the samples, respectively. As shown in Fig. 3, the pesticide use intensity for farmers with smartphone access is higher than for farmers without smartphone access under the low digital economy development scenario but higher under the high digital economy development scenario. Also, the intensity of pesticide use under the high digital economy development scenario is lower than under the low digital economy development scenario. The results in Fig. 3 confirm the double-edged sword effect of smartphone access on pesticide use intensity observed by several empirical studies in China.

4.3. Endogeneity test results

Table 4 presents the endogeneity test results using the panel data. We follow the mature method and perform the first stage estimation to test the correlation between the instrumental and endogenous variable (Wooldridge et al., 2016). Based on the first stage estimation, the coefficient for the instrumental variable is 0.1331 and is statistically significant at a 99 % confidence level. This result indicates that the smartphone usage rate in the village would increase smartphone access and shows that the instrumental variable satisfies the requirement of correlation with the endogenous variable.

The second stage confirms the findings on the significant and positive impacts of smartphone access on pesticide use intensity. According to previous literature (Stock and Yogo, 2002), we utilize the squared t-statistic of the regression coefficient for the instrumental variable from the first-stage regression, denoted as the F-value, to determine whether there is a weak instrument problem. The results indicate that the F-value is 11.297,[4] which exceeds 10, suggesting that this study has no weak instrument problem.

5. Discussion

The understanding of the impacts of smartphone access on pesticide use intensity has been paradoxical. Some research argued that the integration of smartphones into agricultural production and management allows farmers to access agricultural knowledge and product information to develop smart and precision agriculture and offers opportunities to properly use pesticides and achieve pesticide reduction goals (Rotz et al., 2019; Clapp and Ruder, 2020). However, some empirical studies found that smartphone access did not reduce but, in some cases, even increased pesticide use intensity (Ma and Zheng, 2022).

Our empirical assessment results explain such a paradox. Overall, smartphone access hasn't helped reduce pesticide use in China yet: rural households with smartphone access had 8 % higher pesticide use intensity than those without smartphone access. Our findings suggest that not only smartphone access but also the development in digital economy significantly affects the intensity of pesticide use. Smartphone access in the regions with a higher level of development in digital economy helps lower the pesticide use intensity in China. The overall increase in the intensity of pesticide use associated with smartphone access in China was primarily due to the significant increases in pesticide use intensity in those regions with lower levels of development in digital economy. The results are robust, as the regression coefficients from the fixed effect models are fairly consistent.

Empirical results indicate that smartphone access must be accompanied by a high level of development in digital economy to reduce farmers' pesticide use. However, the regions with a low development level of digital economy in China generally have insufficient digital infrastructure, which results in poor network communication, weak network signal coverage, slow network speed, and nearly no existence of content creation and other supporting services. Without the public agricultural extension services, pesticide sellers have been the primary source for most farmers to gain pesticide product information and application knowledge in China (Fan et al., 2015; Jin et al., 2015). Because of the lack of digital infrastructure, the farmers with smartphone access still mainly obtain information through phone calls and SMS text messages, as in the case of Papua, Indonesia (Heimerl et al., 2015). The CFD also shows that households with smartphone access are financially better off and socially better connected than those without smartphones. Therefore, they are more willing and able to take risks and increase pesticide use intensity.

However, in regions with a high level of development in digital economy, smartphones are a new tool in agricultural operations and profoundly impact agricultural productivity. Farmers can rely on smartphones to independently search and access online information on resources and products related to agricultural production. Diverse forms of information such as text, pictures, voice, and video also help farmers break through many traditional barriers imposed by limited education, lack of social connections, and spatial isolation to learn more about crops and pesticides so that they can more properly use the products to improve the efficiency of pesticide use and, in many cases, reduce pesticide use. The flow of knowledge and information on social media then stimulates the growth of local digital services and content creation in the rural areas in those regions. Many experienced farmers become content creators to share their experiences and knowledge of using pesticides through short videos, live broadcasts, online courses, and other means (Šūmane et al., 2018). Such localized content and services have been proven to be very effective in influencing farmers' decision in pest control and disease prevention (Carolan, 2022).

The findings of this study have important implications for achieving China's pesticide reduction goals. First, smartphone access has a great potential to reduce the intensity of pesticide use; however, the potential can only be realized with the development of the local digital economy and the support of digital infrastructure. Therefore, to reduce the intensity of pesticide use, governmental policies should focus on increasing farmers' access to smartphones and other smart terminals such as tablets and investing in digital infrastructure to promote the development of the local digital economy. Second, after China decommissioned its public agricultural extension system in the 1980s, agricultural resource suppliers essentially filled the void left by the public extension system and became the sole source of agricultural knowledge and product information for farmers who seek advice, which causes pesticide overuse in China (Wang and Gu, 2013). In this digital transformation era, Chinese governments must build the public digital agricultural extension system by investing in app development, content creation and network building to disseminate scientific knowledge on pesticides and their proper uses. The governments may also encourage more experienced farmers to get involved in media content creation and become technical experts in local digital communities to promote peer learning and knowledge sharing. Third, the farmers need to be trained

[4] The calculation formula is: $F = t^2 = \left(\frac{0.1331}{0.0396}\right)^2 = 11.297$.

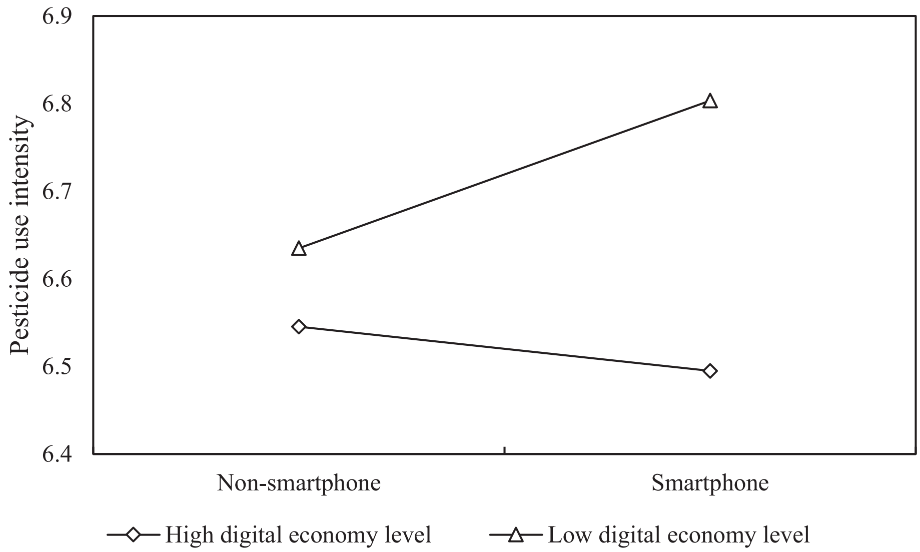


Fig. 3. The impacts of digital economy development on pesticide use intensity.

Table 4
Endogeneity test results excluding the top 1 % of households in pesticide use intensity, total sown area, and agricultural income per capita.

	(1)	(2)
	Smartphone	Pesticide use intensity
Smartphone		1.3570*
		(0.7327)
Instrumental Variable	0.1331***	
	(0.0396)	
Age	−0.0182***	0.0235*
	(0.0013)	(0.0137)
Education	0.0057***	−0.0075
	(0.0021)	(0.0067)
Gender	0.0446*	−0.0574
	(0.0228)	(0.0657)
Ratio of agricultural employment	0.0326	0.0158
	(0.0269)	(0.0699)
Ratio of staple food crops	−0.0114	0.4232***
	(0.0444)	(0.1096)
Agricultural loan	−0.0055	0.0867
	(0.0344)	(0.0847)
Production for self-consumption	−0.0153	−0.0457
	(0.0194)	(0.0491)
Farmland certification	−0.0131	−0.0267
	(0.0174)	(0.0441)
Agricultural guidance	0.0288	−0.0029
	(0.0265)	(0.0682)
Total sown area	0.0761**	−1.6134***
	(0.0349)	(0.1030)
Annual per capita income of the village	−0.0052	−0.0234
	(0.0088)	(0.0219)
Distance from market	−0.0018	−0.0247
	(0.0094)	(0.0231)
Household fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
N	7900	7900
R^2	0.2843	0.0805
F	54.49	–

Note: Significance levels: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$. The sample size is obtained after excluding observations with missing values.

on how to use smartphones to access the necessary information since the general education level of the farmers is low in China. According to the China Internet Network Information Center, a lack of user skills, even the basic keyboard input skills, often prevents many rural residents from accessing and effectively using the Internet.

6. Conclusion

This study examines the relationship between smartphone access and pesticide use intensity among rural households in China based on the Zhejiang University Chinese Family Database in 2015, 2017, and 2019. The results show that smartphone access increased pesticide use intensity among the sampled rural households in China in those periods. However, the impacts were mediated by the level of development in regional digital economy and vary across different regions in China. In the regions with low levels of development in digital economy, smartphone access intensifies pesticide use. However, in the regions with high levels of development in the digital economy, smartphone access helps reduce the intensity of pesticide use. Rural households in rural regions with a high level of development in digital economy can use smartphones to access all different contents on pesticides and their proper use, develop knowledge on crop disease prevention and pest control, and ultimately reduce the pesticide use intensity. The study results demonstrate the potential of digital technologies, such as smartphone access, to reduce the intensity of pesticide use. However, substantial work is needed to realize such potential. This work includes developing regional and local digital infrastructure, rebuilding the public agricultural extension services, and foundational training on farmers to use smartphones.

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CRediT authorship contribution statement

Lin Xie: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Zeyuan Qiu:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Shuyin Chen:** Methodology, Formal analysis, Data curation. **Xiao Lei:** Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.173867.

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