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Factors influencing smartphone usage of rural farmers: Empirical analysis of five selected provinces in China

Wanglin Ma
Lincoln University, Christchurch, New Zealand

Enoch Owusu-Sekyere
Swedish University of Agricultural Sciences, Uppsala, Sweden
University of Pretoria, South Africa
University of the Free State, Bloemfontein, South Africa

Hongyun Zheng
Huazhong Agricultural University, Wuhan, China

Victor Owusu
Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana

Abstract
The increasing usage of smartphones by practitioners in various fields of expertise is attracting global attention. However, scanty evidence exists on smartphone usage among rural farmers in developing countries. Using data collected from 1286 rural farming households in five provinces in China, this study investigates the factors influencing rural farmers' decisions to use smartphones. The findings from a Probit model reveal that education, health condition, asset ownership, income levels, peers' smartphone usage, internet access, cooperative membership, access to credit, and off-farm work participation are the main factors driving smartphone usage of rural farmers. The age of the farmer rather affects smartphone usage negatively and significantly. Further heterogeneous analysis shows that the influences of factors on smartphone usage vary across the survey provinces.

Keywords
smartphone usage, probit model, influencing factors, rural farmers, China

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Introduction

Smartphone usage is increasing swiftly around the globe. A global survey by Bankmycell (2022) reported that the number of people subscribing to use smartphones has increased from 4.44 billion in 2017 to 6.34 billion in 2021. It is projected that the number of smartphone users will surpass 7.52 billion by the year 2026 and 72% of all internet users will solely use smartphones to access the web by 2025 (Bankmycell, 2022). Despite the increasing number of smartphone users, the market penetration of smartphones in populous Asian countries remains low. For example, in 2021, the smartphone penetration rates in China, India, Indonesia, Pakistan and Bangladesh are 64%, 32%, 59%, 18% and 32%, respectively (Bankmycell, 2022). The growth in usage and subscription to smartphones vary across countries or within them. Smartphone ownership is more common among men (relative to women),

Corresponding author:
Hongyun Zheng, College of Economics & Management, Huazhong Agricultural University, Wuhan, China.
Email: Hongyun.Zheng@mail.hzau.edu.cn

people aged 18–49, urban residents (relative to rural residents), and highly educated and high-income earners (Bankmycell, 2022). In addition, due to lagged information and communication technology (ICT) infrastructure construction, the penetration rate of smartphone usage in rural regions is relatively lower than that in urban regions. Notably, the smartphone market still has the potential to grow, especially in rural areas.

A growing number of studies in various fields of study have investigated the factors affecting smartphone usage among people (Gao et al., 2015; Han et al., 2006; Harkke, 2006; Park et al., 2013; Park and Chen, 2007; Tahamtan et al., 2017). Studies on medical practitioners in the United States (Park and Chen, 2007), Iran (Tahamtan et al., 2017), and Finland (Han et al., 2006; Harkke, 2006) revealed that perceived usefulness and the ease of smartphone usage are the key factors influencing people's acceptance and usage. Some studies have also linked smartphone usage to behavioural and psychological factors among specific age groups. For example, Jiang and Li (2018) found that self-esteem, leisure, boredom, and sensation-seeking are crucial factors that affect youth dependency on smartphones in China. Lay-Yee et al. (2013) found that purchase decisions, price, brand, convenience, product features, and social influence are primary determinants of purchasing smartphones among the Malaysian generation. From a psychological viewpoint, individuals' desire for novelty, innovativeness, and intensity are also associated with their smartphone usage behaviour (Jensen et al., 2011; Park et al., 2013; Shi et al., 2011). Park et al. (2013) argued that the usage of smartphones by South Koreans could be explained by people's psychological constructs, such as the desire for social inclusion, locus of control, and perceived relationship control.

Even though smartphone usage among rural farmers is projected to be low relative to people dwelling in cities and urban areas (Bankmycell, 2022; Silver and Cornibert, 2019), it is significant to accelerate smartphone usage penetration in rural areas. This is because agriculture is still the traditional economic activity among the rural population in many developing countries. Smartphone technology plays an increasingly important role in improving the sustainable development of the agricultural sector through accessing relevant production, marketing and climate information, and precision agriculture technologies (Kamilaris and Pitsillides, 2016; Ma et al., 2020; Ma and Zheng, 2022; Michels et al., 2020; Schulz et al., 2022; Vellidis et al., 2016). For example, farmers could use smartphone technologies with soil moisture sensors to determine the accurate timing of irrigation (Vellidis et al., 2016). In livestock farming, farmers could use precision livestock farming sensors installed on smartphones to monitor livestock movements, feeding, and disease detection. The use of smartphone applications (apps) among Australian livestock farmers facilitates farmer extension, training and on-farm decision-making (Schulz et al., 2022).

To the best of the authors' knowledge, only four studies (Bonke et al., 2018; Hallau et al., 2018; Kosta et al., 2015; Michels et al., 2020), three from the same developed country (i.e., Germany) and one from a developing economy (i.e., Serbia), have investigated the demographic and social-economic factors that affect rural people's decisions to use smartphones. Specifically, Michels et al. (2020) explored the drivers of German farmers' usage of smartphones and found that farmers' age, education, and farm size are determinants of smartphone usage. Bonke et al. (2018) examined experienced German farmers' willingness to pay for smartphone apps for crop protection, while Hallau et al. (2018) examined the automated use of smartphones to detect sugar beet disease in Germany. Kosta et al. (2015) investigated the use of smartphone android applications for agricultural machinery in Serbia.

The present study contributes to narrowing the gap in the literature on smartphone usage by investigating the factors affecting rural farmers' usage of smartphones in developing countries, taking China as a case study. Specifically, we want to answer two research questions: (1) What are the factors influencing farmers' decisions to use smartphones? And (2) Whether the factors affecting farmers' smartphone use decisions are heterogeneous across the survey provinces. The answers to these questions will contribute to expanding the knowledge of technological advancement in rural areas by identifying the critical drivers of modern mobile information technology adoption. The diffusion of digital technologies in rural areas of China has lagged behind urban areas (CNNIC, 2022), and narrowing the urban-rural digital divide is a prerequisite for supporting sustainable social development. Insights from the study can also potentially help governments and smartphone developers and manufacturers to design rural farmer-targeted interventions and programs, promoting the widespread usage of smartphones in China.

This paper is structured as follows. The next section discusses the literature review. Section 3 presents the analytical framework and the empirical model. Section 4 discusses the data collection and the selection of variables. The results are presented and discussed in Section 5. The final section concludes and proposes the policy recommendations.

Literature review

Benefits of smartphone usage

Smartphone usage is associated with many benefits. These include, for example, easy access to useful information, having entertainment with games, music, or movies, socialization and fast communications through emails and other chatting apps (e.g., WeChat, QQ, Instagram, WhatsApp, and Facebook), online shopping, and managing mobile money system (Bae, 2019; Hubert et al., 2017; Nie et al., 2021; Zheng and Ma, 2023). The benefits associated with not using smartphones could be potential hazards that can be prevented from not using them. For example, smartphone usage may leak the personal information of users, and addictive smartphone usage wastes productive time. Long-term usage of smartphones may cause severe eyestrain and retina damage, as well as psychological issues (e.g., loneliness, feeling self-centred, and being suspicious all the time) (Horwood and Anglim, 2019; Rotondi et al., 2017; Rozgonjuk et al., 2018; Vahedi and Saiphoo, 2018).

A growing number of scholars in China have investigated the social and psychological effects of smartphone usage, helping us better understand the roles of smartphones in influencing social development. Although excessive and addictive smartphone usage increases health risks (Guo et al., 2022; Huang et al., 2020; Mei et al., 2023), most scholars argue that appropriate usage can generate significant benefits by improving users' incomes and subjective wellbeing and facilitating farmers' adoption of environmentally-friendly practices (Chan and Li, 2020; Li et al., 2022; Ma et al., 2020; Nie et al., 2021; Tang et al., 2023; Zheng and Ma, 2023). For example, Ma et al. (2020) found that smartphone use increases farm income, off-farm income and household income of rural households in China. They also found that smartphone use has a larger income effect for male household heads and male off-farm work participants relative to their female counterparts. Chan and Li (2020) showed that smartphones support people's access to mobile short message services, emails, Weibo and WeChat for social communications, improving users' psychological well-being. Li et al. (2022) reported that smartphone usage motivates farmers to adopt a rice-green manure rotation system (a type of agricultural conservation practice) because smartphone apps help farmers access environmental information and improves their knowledge and awareness of environmental degradation. Despite the significant findings in the literature reviewed above, little attention has been paid to investigating how rural farmers' decisions on smartphone usage in China are influenced by their personal characteristics, farm and household characteristics, social-economic characteristics and location-specific characteristics. The present study attempts to fill in this knowledge gap.

Hypotheses on factors influencing smartphone usage

Figure 1 demonstrates the factors that influence farmers' decisions to use smartphones. This study discusses those factors and their expected signs from four aspects, including farmer characteristics (age, education, gender, and health), farm and household characteristics (family size, asset ownership, income, and farm size), social-economic characteristics (peer effects, access to internet, cooperative membership, access to credit, and off-farm work), and location-specific characteristics (distance to market, transportation, and geographical locations).

Farmer characteristics. Age is expected to have a negative effect on smartphone usage because existing studies have shown that the younger generation tends to have a high interest in adopting new technologies (Bankmycell, 2022; Tamirat et al., 2018). Education is expected to affect smartphone usage positively. Studies by Carrer et al. (2017) and Walton et al. (2008) revealed that better-educated farmers are more likely to adopt precision technologies. In addition, better-educated farmers have a higher tendency to search, collect, process, and use information mostly accessed through smartphones (Zheng and Ma, 2023). In terms of gender, Adamides et al. (2013) found that male farmers are more likely to adopt new innovations, such as computers in agriculture, relative to females. Female farmers usually lack resources and financial capital. Therefore, this study expects the gender variable, representing male farmers (male = 1), to affect smartphone usage

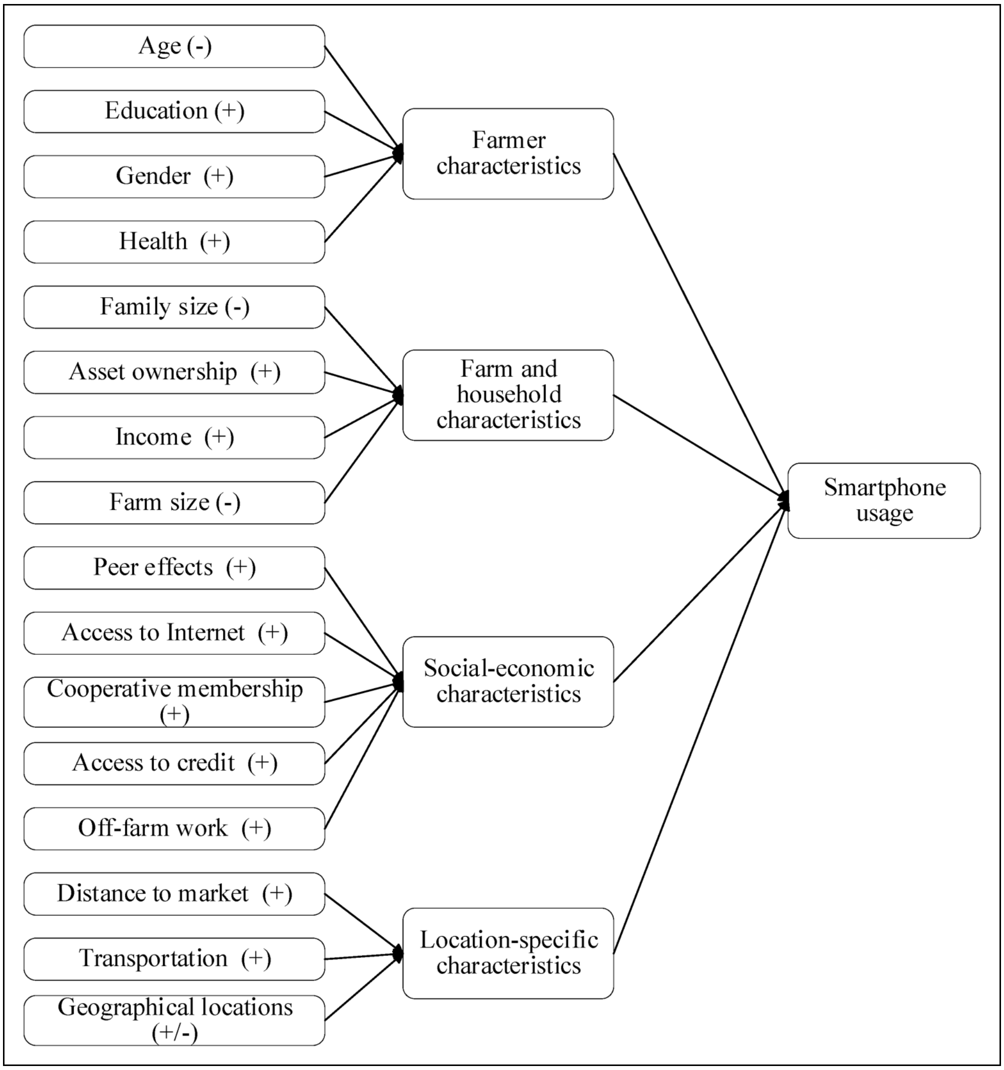

Figure 1. Potential factors affecting farmers' decisions on smartphone usage and expected signs data source: CSY, 2020.

positively. A better health condition is expected to be associated with a higher probability of using a smartphone. Healthier farmers are usually endowed with a higher working capacity and human capital (Loureiro, 2009), encouraging them to adopt innovative technologies, such as smartphones.

Farm and household characteristics. Family and farm sizes are expected to have negative effects on smartphone usage since large households and farms need higher expenditures. As such, farmers are more likely to invest in their family members (e.g., children and elders) and farms than to purchase "luxury" technologies such as smartphones (Koundouri et al., 2006). Ownership of assets such as micro-ovens is expected to influence the probability of smartphone usage positively. Asset ownership is a proxy of household wealth (Fischer and Qaim, 2012), and wealthy people are more likely to afford the purchase of smartphones. In terms of income, this study expects that farmers with higher income levels are more likely to use smartphones since they have high purchasing power compared to those with lower income levels (Bankmycell, 2022; Carrer et al., 2017).

Social-economic characteristics. Consistent with the existing studies showing that peer effects positively affect the adoption of new technologies (Allcott and Kessler, 2019; Bollinger and Gillingham, 2012), peers' smartphone usage status is expected to positively affect farmers' smartphone usage. Internet access is expected to have a positive effect on smartphone usage since most smartphone apps require the internet, particularly WIFI, to operate. Thus, households with internet access are more likely to use smartphones (Philip et al., 2017). Membership in an agricultural cooperative is expected to have a positive effect on smartphone usage. Studies by Allcott and Kessler (2019) and Bailey et al. (2018) have indicated that sharing information about innovative technologies influences smartphone usage. Credit access is expected to positively affect smartphone usage since access to credit enhances the purchasing power of farmers and increases the adoption of new technologies (Mohamed and Temu, 2008). Participation in off-farm work is expected to have a positive effect on smartphone usage. Koundouri et al. (2006) argued that income gained from off-farm work could be invested in new technologies (income effect).

Location-specific characteristics. Distance to the nearest input market (km) and distance to the train station (km) are expected to affect smartphone usage positively. This is because households that are farther from input markets can check input and output prices and order inputs online using smartphones. Similarly, those residing far away from train stations could rely on their smartphones for checking departure and arrival times as well as for ticket purchases. Finally, the location of the smallholder farmer plays a significant role in smartphone usage. For example, some rural areas do not have digital infrastructure to provide mobile internet access, restricting the diffusion of smartphone technology (Philip et al., 2017). Therefore, the location dummies are also included to capture the location-fixed heterogeneities that affect smartphone usage without assigning prior signs.

Analytical framework and empirical model

In the present study, the smallholder farmers' decisions to use smartphones are modelled as a dichotomous choice. The study assumes that farmers are rational and make smartphone-use decisions to maximize the expected benefits. A farmer i would compare the expected benefits associated with smartphone usage (S_U^*) with the benefits associated with not using smartphones (S_N^*). A farmer will choose to use the smartphone if he/she perceives the expected benefit from using it (S_U^*) is higher than that from not using it (S_N^*). Let SU_i^* be the difference between the expected benefits of using and not using smartphones; one can obtain $SU_i^* = S_U^* - S_N^* > 0$. The expected benefits are subjective, so they cannot be measured or observed directly. Alternatively, farmers' decisions to use smartphones could be modelled by a latent variable function specified as follows:

$$SU_i^* = \beta X_i + \mu_i,\ SU_i = \begin{cases} 1, & SU_i^* > 0 \\ 0, & Otherwise \end{cases} \quad (1)$$

where SU_i^* represents the propensity of smartphone usage, which is captured by an observed variable SU_i. SU_i takes the value of 1 if randomly chosen farmer i uses a smartphone in 2018 and 0 otherwise. X_i denotes the explanatory variables (e.g., age, gender, education, income levels, and internet access) included in the model. The estimators of β capture the effects of changes in the explanatory variables on the probability of a farmer using a smartphone. The error term is denoted by μ_i.

When the dependent variable (smartphone usage) is dichotomous, Equation (1) can be estimated using either a Probit or Logit model (Stock and Watson, 2012). Econometrically, both Logit and Probit models yield similar coefficients, marginal effects, and conclusions (Dill et al., 2015). The only difference between the Logit model and the Probit model lies in the assumptions about the distributions of the errors. Specifically, the error term of the Probit model is assumed to have a commutative standard normal distribution function, while the error term of the Logit model is assumed to have a cumulative logistic distribution function (Wooldridge, 2010). The Probit model is employed in the present study. The probability of being a smartphone user can be expressed as:

$$\begin{aligned} \Pr(SU_i = 1) &= \Pr(SU_i^* > 0) = \Pr(\mu_i > -\beta X_i) \\ &= 1 - F(-\beta X_i) \end{aligned} \quad (2)$$

where F is the commutative distribution function for μ_i.

Data collection

Survey sites

The empirical analysis of this study relies on cross-sectional household survey data collected from five provinces in China, namely Shandong, Fujian, Anhui, Henan, and Sichuan. The selected provinces were heterogeneous in the demographic and socio-economic characteristics of rural households and levels of rural development in China. For example, the per capita disposable income and per capita consumption expenditure were the highest in rural areas of Fujian province among the five survey provinces in 2019, which were 19,570 Yuan (about 3028

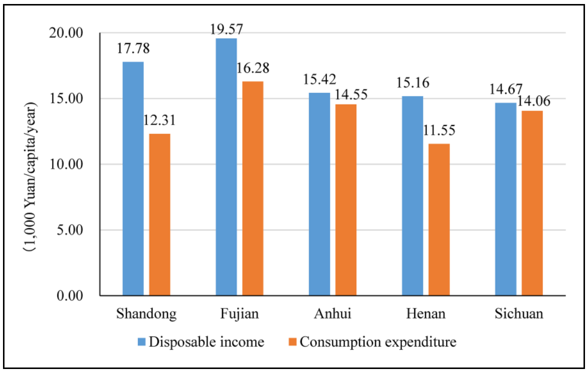

Figure 2. Disposable income and consumption expenditure in survey provinces in 2019.

USD) and 16,280 Yuan (about 2519 USD), respectively (see Figure 2) (CSY, 2020). Rural people in Sichuan province received the lowest per capita disposable income, which was 14,670 Yuan (about 2270 USD). The per capita consumption expenditure of rural people in Henan was the lowest, which was 11,550 Yuan (about 1787 USD). The notable differences across the selected provinces make the samples used in the present study nationally representative, which helps to enhance the generalization of the implications of the study's findings.

Sampling approach

Data were collected between January and July 2019 from 1286 rural households using a multistage sampling procedure. First, this study selected the aforementioned five provinces (Shandong, Fujian, Anhui, Henan, and Sichuan) from different geographical locations (eastern, central, and western China). Shandong and Fujian are randomly selected from the Eastern region, Anhui and Henan are randomly selected from the Central region, while Sichuan is randomly selected from the Western region. Then, two cities were randomly selected in each province, and then two to three towns in each city. Thirdly, around two to three villages in each town were randomly selected. Finally, in each village, about 10 to 30 rural residents were randomly selected in consideration of the village sizes. The respondents were all farmers, producing various crops (e.g., wheat, potato, maize, and rice) for their livelihoods. Farmers were interviewed face-to-face by well-trained enumerators using a structured questionnaire. Since the objective of this study was to explore the factors affecting smartphone usage of rural farmers, the respondents were asked to report their smartphone usage status in 2018. Precisely, smartphone usage is measured as a dichotomous variable, which equals 1 if a respondent is a smartphone user and 0 otherwise.

Results and discussions

Descriptive results

The definition and descriptive statistics of the variables used in the empirical model in Equation (1) are provided in Table 1. The summary statistics show that around 62% of the sampled farmers used smartphones in 2018, indicating a broad application of smartphones in rural China. The surveyed farmers have an average age of 53 years old. The average number of years of formal education is about 6 years, which implies that smallholder rural farmers in China have a low level of education. A total of 63% of them are males. The reported health score is 3.8 out of 5, indicating that the respondents generally have good health conditions. Regarding farm and household characteristics, Table 1 shows that the proportion of households with micro-oven ownership is about 23% of the total sample. The sampled households have approximately five members and cultivated 9.55 mu land for agricultural production. Approximately 62% of peers within the same village are smartphone users. About 59% of the sampled respondents have access to the internet. The proportion of households with access to credit is 22% of the total sample, and 44% have participated in off-farm works. The average distance covered by the smallholder farmers to reach the nearest input market is about 33 kilometres.

To further explore the smartphone penetration rates across the survey provinces, this study depicts the proportions of smartphone users and non-users by provinces in Figure 3. It shows that among the five survey provinces, the proportion of smartphone users is the highest in Anhui and that in Henan is the lowest, representing 79.34% and 42.18%, respectively. In Shandong, Fujian, and Sichuan, smartphone users account for 46.07%, 71.95%, and 50.22% of surveyed samples, respectively. Fujian and Anhui have the lowest proportions of non-users of smartphones, representing 28.05% and 20.66% of the surveyed samples, respectively. These notable differences in smartphone usage proportions across the survey provinces tend to suggest that factors affecting smartphone use vary

Table 1. Variable definitions and summary statistics.

Variables	Definitions	Mean (S.D.)
Dependent variable		
Smartphone usage	1 if respondent used smartphone in 2018, 0 otherwise	0.62 (0.49)
Independent variables		
Farmer characteristics		
Age	Age of respondent (years)	53.10 (11.93)
Education	Education years of respondent (years)	5.87 (3.85)
Gender	1 if respondent is male, 0 otherwise	0.63 (0.48)
Health	Self-reported health status of respondent from 1 = very unhealthy to 5 = very healthy	3.80 (1.04)
Farm and household characteristics		
Family size	Number of family members (persons)	4.70 (2.05)
Farm size	Total farm size for agricultural production (mu)[a]	9.55 (17.35)
Asset ownership	1 if household owns micro-oven(s), 0 otherwise	0.23 (0.42)
Income	Total household income (1000 yuan/capita)[a]	17.05 (20.70)
Social-economic characteristics		
Peer effects	Ratio of smartphone users to the number of other respondents within the same village	0.62 (0.24)
Access to Internet	1 if household has access to the Internet, 0 otherwise	0.59 (0.49)
Cooperative membership	1 if household has memberships in any agricultural cooperatives, 0 otherwise	0.09 (0.28)
Access to credit	1 if household has access to credit, 0 otherwise	0.22 (0.41)
Off-farm work	1 if respondent participated in any off-farm work in 2018, 0 otherwise	0.44 (0.50)
Location-specific characteristics		
Distance to market	Distance to the nearest input market (km)	3.81 (4.43)
Transportation	Distance to the nearest train station (km)	33.29 (22.54)
Shandong	1 if household resides in Shandong province, 0 otherwise	0.21 (0.41)
Fujian	1 if household resides in Fujian province, 0 otherwise	0.17 (0.38)
Anhui	1 if household resides in Anhui province, 0 otherwise	0.11 (0.32)
Henan	1 if household resides in Henan province, 0 otherwise	0.33 (0.47)
Sichuan	1 if household resides in Sichuan province, 0 otherwise	0.17 (0.38)
Observations		1286

Note: Figures presented in column 3 refer to means and standard deviations (in parentheses), respectively.
[a]1 mu = 1/15 hectare.

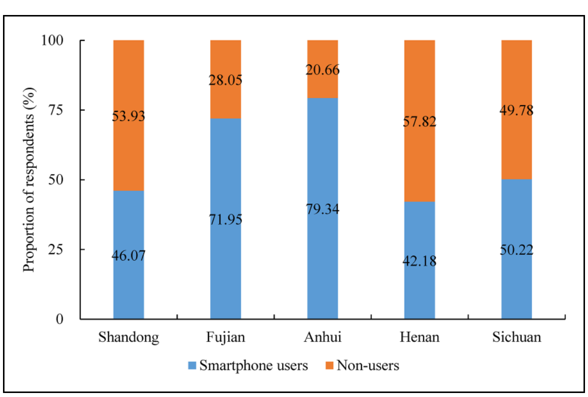

Figure 3. Proportions of smartphone users and non-users in survey provinces.

across the survey provinces. Therefore, this study explores this phenomenon of smartphone usage empirically.

Empirical results

Factors influencing smartphone usage. In this section, the empirical results are presented and discussed. The coefficient estimates of the Probit model are presented in column 2 of Table 2. Because the coefficient estimates are not straightforward in interpretation, the marginal effects of the variables are also calculated and presented in the last column of Table 2. The marginal effect results summarize how the change in our response variable is associated with the change in any of the covariates in our model (Stock and Watson, 2012). In general, the estimated coefficients of the variables in Table 2 have the expected signs.

Among the explanatory variables, the results show that the coefficient of age is negative and statistically significant, implying that the likelihood of farmers' smartphone usage decreases as age increases.

Table 2. Determinants of smartphone usage: probit model estimation.

Variables	Coefficients	z-score	Marginal effects	z-score
Constant	1.800 (0.484)***	3.719		
Farmer characteristics				
Age	−0.080 (0.007)***	−12.116	−0.013 (0.001)***	−14.859
Education	0.120 (0.018)***	6.712	0.019 (0.003)***	7.463
Gender (male)	0.053 (0.124)	0.431	0.009 (0.020)	0.430
Health	0.115 (0.050)**	2.322	0.019 (0.008)**	2.325
Farm and household characteristics				
Family size	0.005 (0.025)	0.209	0.001 (0.004)	0.209
Farm size	0.000 (0.003)	0.185	0.000 (0.000)	0.185
Asset ownership	0.234 (0.142)*	1.641	0.038 (0.023)*	1.649
Income Tertile 2	0.304 (0.129)**	2.358	0.049 (0.021)**	2.405
Income Tertile 3	0.387 (0.124)***	3.114	0.063 (0.020)***	3.179
Social-economic characteristics				
Peer effects	0.892 (0.296)***	3.012	0.145 (0.048)***	3.037
Access to Internet	0.907 (0.113)***	8.027	0.147 (0.016)***	8.956
Cooperative membership	0.467 (0.173)***	2.696	0.076 (0.028)***	2.703
Access to credit	0.260 (0.137)*	1.894	0.042 (0.022)*	1.917
Off-farm work	0.341 (0.121)***	2.808	0.055 (0.020)***	2.821
Location-specific characteristics				
Distance to market	0.006 (0.012)	0.513	0.001 (0.002)	0.514
Transportation	0.004 (0.003)	1.564	0.001 (0.000)	1.568
Shandong	−0.028 (0.163)	−0.173	−0.005 (0.027)	−0.173
Fujian	0.480 (0.204)**	2.356	0.078 (0.033)**	2.379
Anhui	0.036 (0.188)	0.190	0.006 (0.031)	0.190
Henan	0.234 (0.194)	1.209	0.038 (0.031)	1.212
Statistics				
Pseudo-R^2	0.563			
Chi-square	391.43			
Log-likelihood	−373.487			
Observations	1286			

Note: *** < 0.01, ** < 0.05, * < 0.10. Robust standard errors are presented in parentheses. The reference province is Sichuan. Income tertile 1 is used as the reference group.

The marginal effect of the age variable suggests that one year increase in farmers' age, on average, leads to a reduction of 0.013 in the probability of using a smartphone. This finding agrees with the finding of Michels et al. (2020) on Germany, demonstrating that older farmers are less likely to acquire information through smartphones. D'Antoni et al. (2012) also found that young farmers are more inclined to modern technologies and are more likely to use smartphones compared to older farmers. The coefficient and the marginal effect of the education variable are positive and statistically significant. The coefficient suggests that well-educated farmers are more likely to use smartphones. Precisely, the marginal effect indicates that one year increase in farmers' education, on average, increases the probability of smartphone usage by 1.9%. This finding is consistent with previous studies by Poolsawas and Napasintuwong (2013). Better educated farmers are more able to understand and use information about smartphone applications and technologies than the less educated.

The health variable exhibits a statistically significant and positive coefficient and marginal effect. This implies that farmers with a higher level of health conditions are more likely to use smartphones than their counterparts with a lower levels of health conditions. The coefficient and the marginal effect of the asset ownership variable are positive and significantly different from zero. The marginal effect of 0.038 suggests that, on average, farmers who have microwave ovens (a proxy of the household asset that reflects rural household wealth) are 3.8% more likely to use smartphones than farmers who do not own a microwave oven. This finding is supported by Zheng and Ma (2023), who found that ownership of microwave ovens positively affects the acquisition of smartphone-based information in China. The variables representing income tertiles 2 and 3 variables are positive and significantly different from zero, suggesting that farmers within the middle and high-income tertiles are more likely to use smartphones. Farmers at the income tertile 2 are 4.9% more likely to use smartphones than those at the income tertile 1 (reference group). Also, farmers at the income tertile 3 are 6.3% more likely to use smartphones than those at the lowest income tertile 1. These findings are in line with Carrer et al. (2017), who found that farmers with high income and production revenue are more likely to adopt computer technology in Brazil.

The results show that peer effects positively and significantly affect smartphone usage. The finding suggests that the usage of smartphones by other farmers in the village leads to an increase in an individual farmer's propensity to use smartphones. Specifically, the marginal effect for this variable indicates that a 10% increase in the ratio of smartphone users to the number of other respondents within the same village, on average, increases the probability of farmers' smartphone usage by 1.45%. This result is consistent with Bailey et al. (2018), who found that the demand for cell phones, including smartphones, is positively influenced by peer effects in the United States and Canada. The finding is further supported by Bollinger and Gillingham (2012), who revealed that peer effects positively affect the adoption of new technologies in California, the United States. The results also reveal that farmers with access to the internet are 14.7% more likely to use smartphones than their counterparts with no internet access. Because apps on smartphones require the internet to operate, farmers with internet access are more likely to use smartphones.

The coefficient and marginal effect of membership in agricultural cooperatives are significantly positive. The marginal effect suggests that farmers who are cooperative members are 7.6% more likely to use smartphones than non-members of any cooperative group. Studies by Allcott and Kessler (2019) and Bailey et al. (2018) report similar findings. These studies pointed out that members of agricultural cooperatives tend to share information about innovative technologies, which tends to influence their smartphone usage. The marginal effect of credit access is significantly positive, implying that smallholder rural farmers with access to credit are 4.2% more likely to use smartphones. This finding is supported by Mohamed and Temu (2008), who argued that access to credit enhances the purchasing power of farmers and increases the adoption of new technologies. The coefficient and marginal effect of the off-farm work variable are positive and significant, implying that participation in off-farm work by rural farmers tends to increase their use of smartphones. The marginal effect indicates that farmers who participate in off-farm work in China are 5.5% more likely to use smartphones than those who do not participate in off-farm work. This finding is supported by Koundouri et al. (2006) and Ma et al. (2018), who argued that income gained by farmers from off-farm employment could be used for investing in new and innovative technologies. The results also indicate that smallholder farmers residing in Fujian province are 7.8% more likely to use smartphones than those residing in Sichuan (reference location).

Heterogeneous analysis by survey provinces. Figure 3 demonstrates significant differences in the proportions of smartphone users and non-users across the survey provinces. Here, this study checks whether the selected control variables have homogenous or heterogeneous impacts on the smartphone usage of farmers residing in different provinces. The empirical results (marginal effects) are presented in Table 3. Regarding farmer characteristics, the estimates show that the negative impacts of age and the positive impacts of education on smartphone usage are homogenous. However, gender and health affect smartphone use differently. Specifically, the marginal effect estimates reveal that male farmers in Fujian are 7.4% more likely to use smartphones relative to their female counterparts. Gender has no significant impact on the smartphone usage of farmers residing in other provinces. Health affects smartphone use of Shandong and Anhui farmers positively and significantly, but it affects smartphone usage of Fujian farmers negatively.

As for farm and household characteristics, the estimates show that an additional increase in household members would significantly decrease the propensities of using smartphones among Anhui and Sichuan farmers by 1.8% and 3.2%, respectively. Family size has no significant impact on smartphone usage of farmers in Shandong, Fujian, and Anhui. Farm size decreases the probability of Fujian farmers' smartphone usage by 0.2%, while it increases the probability of Henan farmers' smartphone usage by 18.1%. Asset ownership significantly increases the probability of smartphone usage of Shandong

Table 3. Determinants of smartphone usage by region: probit model estimations.

Variables	Shandong (Marginal effects)	Fujian (Marginal effects)	Anhui (Marginal effects)	Henan (Marginal effects)	Sichuan (Marginal effects)
Farmer characteristics					
Age	−0.014 (0.002)***	−0.016 (0.002)***	−0.009 (0.003)***	−0.008 (0.001)***	−0.018 (0.002)***
Education	0.018 (0.006)***	0.018 (0.006)***	0.024 (0.007)***	0.019 (0.004)***	0.014 (0.007)*
Gender (male)	0.035 (0.045)	0.074 (0.044)*	−0.043 (0.086)	−0.019 (0.028)	−0.006 (0.048)
Health	0.046 (0.018)**	−0.051 (0.022)**	0.056 (0.024)**	0.017 (0.010)	0.028 (0.019)
Farm and household characteristics					
Family size	0.006 (0.010)	0.010 (0.011)	−0.018 (0.011)*	0.003 (0.005)	−0.032 (0.015)**
Farm size	−0.004 (0.003)	−0.002 (0.001)***	0.013 (0.005)***	0.001 (0.001)	0.002 (0.001)***
Asset ownership	0.105 (0.042)**	0.089 (0.045)**	0.079 (0.057)	−0.114 (0.041)***	−0.008 (0.057)
Income tertile 2	0.063 (0.042)	0.116 (0.047)**	−0.006 (0.057)	−0.009 (0.028)	0.092 (0.053)*
Income tertile 3	0.110 (0.046)**	0.157 (0.040)***	0.047 (0.057)	0.008 (0.030)	−0.042 (0.050)
Social-economic characteristics					
Peer effects	0.098 (0.136)	0.321 (0.109)***	−0.225 (0.191)	0.181 (0.068)***	0.163 (0.181)
Access to Internet	0.129 (0.039)***	0.051 (0.037)	0.153 (0.044)***	0.140 (0.024)***	0.273 (0.036)***
Cooperative membership	0.073 (0.057)	−0.070 (0.051)	−0.082 (0.100)	0.067 (0.048)	0.165 (0.066)**
Access to credit	−0.072 (0.050)	0.166 (0.043)***	0.050 (0.057)	−0.022 (0.025)	0.107 (0.098)
Off-farm work	0.064 (0.038)*	0.073 (0.055)	0.031 (0.068)	0.019 (0.029)	0.106 (0.049)**
Location-specific characteristics					
Distance to market	−0.002 (0.005)	−0.006 (0.006)	−0.017 (0.016)	0.001 (0.003)	0.004 (0.006)
Transportation	0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.000 (0.000)	0.002 (0.002)
Observations	267	221	147	426	225

Note: *** < 0.01, ** < 0.05, * < 0.10. Robust standard errors are presented in parentheses. Income tertile 1 is used as the reference group.

and Fujian farmers, but it significantly decreases the probability of smartphone usage of Henan farmers. Relative to farmers at the income tertile 1 (reference group), Shandong farmers at the income tertile 3, Fujian farmers at the income tertiles 2 and 3, and Sichuan farmers at the income tertile 2 have a higher likelihood of using smartphones.

Regarding social-economic characteristics, the estimates show that the peer effects of smartphone usage have a stronger impact on the probabilities of using smartphones by Fujian and Henan farmers. Cooperative membership exclusively has a significant impact on Sichuan farmers' smartphone usage, and access to credit exclusively exerts a significant impact on Fujian farmers' smartphone usage. Specifically, being a cooperative member increases the probability of smartphone use of Sichuan farmers by 16.5%, and access to credit increases the likelihood of smartphone usage of Fujian farmers by 16.6%. Off-farm work increases the probabilities of smartphone usage among Shandong and Sichuan farmers by 6.4% and 10.6%, respectively. Off-farm work is not significantly associated with smartphone usage decisions of farmers in Fujian, Anhui and Henan. Overall, the finding in Table 3 highlights the importance of capturing the location-fixed effects in investigating the factors influencing Chinese rural farmers' decision to use smartphones.

Conclusions and policy recommendations

Although the smartphone penetration rate is increasing globally, smartphone usage in rural regions has lagged its usage in urban regions. Understanding what drives smallholder rural farmers' usage of smartphones is essential for improving the acceptance and usage of smartphone technology and developing targeted smartphone apps for agricultural purposes. The present paper investigated factors influencing farmers' decisions to use smartphones using data collected from 1286 farming households in five provinces (Shandong, Fujian, Anhui, Henan and Sichuan) of rural China. A Probit model is employed in the empirical analysis.

The results from the empirical analysis revealed that smartphone usage among rural farmers in China is affected by various factors associated with farmer characteristics, farm and household characteristics, social-economic characteristics, and location-specific characteristics. The age of the farmers exhibited a negative effect on the probability of using smartphones. The other two farmer characteristics, including education and health, positively affected the usage of smartphones. Farm and household characteristics that positively influenced the farmers' usage of smartphones include asset ownership and household income. All social-economic factors, including peer effects, internet access, cooperative membership, access to credit, and off-farm work participation, were positively correlated with the usage of smartphones by rural farmers in China. Regarding location-specific effects, rural farmers in the Fujian province are significantly more likely to use smartphones than farmers in Sichuan. Further heterogeneous analysis showed that the influences of factors on smartphone usage vary across the five survey provinces.

Overall, the findings of this study have significant implications for stakeholders and policymakers in China, which is also likely to be important to other developing countries seeking to increase the smartphone penetration rate in rural regions. Smartphone use has the potential to improve agricultural productivity and sustainability through access to relevant production, marketing and climate information, and precision agriculture technologies. These potential benefits can be attained if the adoption rate of smartphones can be enhanced. One of the ways to improve uptake is for policymakers to have a clear understanding of what influences farmers' decisions. First, the results show that there may be some barriers for older and low-educated farmers when using smartphones. This suggests that additional support for perceiving the usefulness of smartphones and reducing the learning costs of smartphone operation is needed for older and low-educated farmers. In practice, the government can cooperate with smartphone companies to design easy-to-use guidelines and rural-targeted applications. Allowance for purchasing smartphones and mobile internet data plans are also helpful to lower barriers to using smartphones. Second, the study's findings that asset ownership and household income both increase the probability of smartphone usage provide a clear implication. Policies promoting economic growth and poverty alleviation would enable rural farmers to invest in high-cost innovative technologies such as smartphones. A practical strategy is to provide farmers with more income-generating activity information, such as local off-farm jobs and extension services on high-value crop production. For developers and providers of smartphones and smartphone applications, the findings provide relevant insights into the characteristics of users, which may enhance or hinder smartphone usage.

Third, although the peer effect's significant and positive impacts do not exist in all selected provinces, identifying and cultivating leading users of smartphones in rural areas is also valuable. In the relationship-connected society of rural China, a leading smartphone user with strong networks would definitely encourage villagers' imitation of smartphone usage. Finally, accelerating internet infrastructure construction in rural areas may help promote smartphone penetration by enabling rural farmers to obtain affordable, high-speed internet services. Since installing broadband internet hook-ups for each rural household may be costly, investing more in wireless internet facilities such as WIFI is an effective and cost-saving way to provide internet services to rural farmers. Furthermore, policymakers and telecommunication companies should expand mobile and fixed broadband coverage, particularly in rural farming communities.

This study estimated cross-sectional data collected from 1286 rural households, which cannot capture the dynamic effects of factors on smartphone usage decisions. As smartphone technology changes over time, it might be interesting for future studies to investigate how various factors affect rural farmers' decisions on smartphone usage dynamically with the use of time-series data or panel data. Also, exploring how (homogenously or heterogeneously) demographic and social-economic factors affect smartphone usage decisions of rural and urban residents could also help enrich our understanding in this field.

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Data availability statement

The data that support the findings of this study are available from Hongyun Zheng upon request.

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ORCID iD

Wanglin Ma https://orcid.org/0000-0001-7847-8459

References

Adamides G, Stylianou A, Kosmas PC, et al. (2013) Factors affecting pc and internet usage by the rural population of Cyprus. *Agricultural Economics Review* 14: 16–36.

Allcott H and Kessler JB (2019) The welfare effects of nudges: A case study of energy use social comparisons. *American Economic Journal: Applied Economics* 11: 236–276.

Bae SM (2019) The relationship between smartphone use for communication, social capital, and subjective well-being in Korean adolescents: Verification using multiple latent growth modeling. *Children and Youth Services Review* 96: 93–99.

Bailey M, Cao R, Kuchler T, et al. (2018) Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives* 32: 259–280.

Bankmycell (2022) How many smartphones are in the world? [WWW Document]. URL https://www.bankmycell.com/blog/how-many-phones-are-in-the-world

Bollinger B and Gillingham K (2012) Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science* 31: 900–912.

Bonke V, Fecke W, Michels M, et al. (2018) Willingness to pay for smartphone apps facilitating sustainable crop protection. *Agronomy for Sustainable Development* 38: 1–10.

Carrer MJ, de Souza Filho HM and Batalha MO (2017) Factors influencing the adoption of farm management information systems (FMIS) by Brazilian citrus farmers. *Computers and Electronics in Agriculture* 138: 11–19.

Chan M and Li X (2020) Smartphones and psychological well-being in China: Examining direct and indirect relationships through social support and relationship satisfaction. *Telematics and Informatics* 54: 101469.

CNNIC (2022) The 50th Statistical Report on China's Internet Development.

CSY (2020) *China Statistics Yearbook*. Beijing.: China Statistics Press.

D'Antoni JM, Mishra AK and Joo H (2012) Farmers' perception of precision technology: The case of autosteer adoption by cotton farmers. *Computers and Electronics in Agriculture* 87: 121–128.

Dill MD, Emvalomatis G, Saatkamp H, et al. (2015) Factors affecting adoption of economic management practices in beef cattle production in Rio Grande do sul state. *Brazil. Journal of Rural Studies* 42: 21–28.

Fischer E and Qaim M (2012) Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya. *World Development* 40: 1255–1268.

Gao S, Yang Y and Krogstie J (2015) The adoption of smartphones among older adults in China, in: International conference on informatics and semiotics in organisations. *Springer*: 112–122.

Guo K, Ma Q, Yao S, et al. (2022) The Relationship Between Physical Exercise and Mobile Phone Addiction Tendency of University Students in China: A Moderated Mediation Model. *Frontiers in Psychology* 13: 730886.

Hallau L, Neumann M, Klatt B, et al. (2018) Automated identification of sugar beet diseases using smartphones. *Plant Pathology* 67: 399–410.

Han S, Mustonen P, Seppanen M, et al. (2006) Physicians' acceptance of mobile communication technology: An exploratory study. *International Journal of Mobile Communications* 4: 210–230.

Harkke V (2006) Impacts of physicians' usage of a mobile information system. *International Journal Of Electronic Healthcare* 2: 345–361.

Horwood S and Anglim J (2019) Problematic smartphone usage and subjective and psychological well-being. *Computers in Human Behavior* 97: 44–50.

Huang Q, Li Y, Huang S, et al. (2020) Smartphone use and sleep quality in Chinese college students: A preliminary study. *Frontiers in Psychiatry* 11: 1–7.

Hubert M, Blut M, Brock C, et al. (2017) Acceptance of smartphone-based mobile shopping: Mobile benefits, customer characteristics, perceived risks, and the impact of application context. *Psychology & Marketing* 34: 175–194.

Jensen JD, Weaver AJ, Ivic R, et al. (2011) Developing a brief sensation seeking scale for children: Establishing concurrent validity with video game use and rule-breaking behavior. *Media Psychology* 14: 71–95.

Jiang Q and Li Y (2018) Factors affecting smartphone dependency among the young in China. *Asian Journal of Communication* 28: 508–525.

Kamilaris A and Pitsillides A (2016) Mobile phone computing and the internet of things: A survey. *IEEE Internet of Things Journal* 3: 885–898.

Kosta G, Mićo O, Rade R, et al. (2015) The rise of smartphones Android applications for agriculture machines, new revolution of farm machinery-field communication? in: Second International Symposium on Agricultural Engineering, ISAE-2015, 9th-10th October 2015, Belgrade-Zemun, Serbia. Proceedings. Faculty of Agriculture, Department for Agricultural Engineering.

Koundouri P, Nauges C and Tzouvelekas V (2006) Technology adoption under production uncertainty: Theory and application to irrigation technology. *American Journal of Agricultural Economics* 88: 657–670.

Lay-Yee KL, Kok-Siew H and Yin-Fah BC (2013) Factors affecting smartphone purchase decision among Malaysian generation Y. *International Journal of Asian Social Science* 3: 2426–2440.

Li F, Yang P, Zhang K, et al. (2022) The influence of smartphone use on conservation agricultural practice: Evidence from the extension of rice-green manure rotation system in China. *Science of the Total Environment* 813: 152555.

Loureiro ML (2009) Farmers' health and agricultural productivity. *Agricultural Economics* 40: 381–388.

Ma W, Grafton RQ and Renwick A (2020) Smartphone use and income growth in rural China: Empirical results and policy implications. *Electronic Commerce Research* 20: 713–736.

Ma W, Renwick A, Nie P, et al. (2018) Off-farm work, smartphone use and household income: Evidence from rural China. *China Economic Review* 52: 80–94.

Ma W and Zheng H (2022) Heterogeneous impacts of information technology adoption on pesticide and fertiliser expenditures: Evidence from wheat farmers in China*. *Australian Journal of Agricultural and Resource Economics* 66: 72–92.

Mei S, Hu Y, Wu X, et al. (2023) Health risks of mobile phone addiction among college students in China. *International Journal of Mental Health and Addiction*.

Michels M, Fecke W, Feil J-H, et al. (2020) Smartphone adoption and use in agriculture: Empirical evidence from Germany. *Precision Agriculture* 21: 403–425.

Mohamed KS and Temu AE (2008) Access to credit and its effect on the adoption of agricultural technologies: The case of zanzibar. *Savings and Development* 32: 45–89.

Nie P, Ma W and Sousa-Poza A (2021) The relationship between smartphone use and subjective well-being in rural China. *Electronic Commerce Research* 21: 983–1009.

Park N, Kim Y-C, Shon HY, et al. (2013) Factors influencing smartphone use and dependency in South Korea. *Computers in Human Behavior* 29: 1763–1770.

Park Y and Chen JV (2007) Acceptance and adoption of the innovative use of smartphone. *Industrial Management & Data Systems* 107: 1349–1365.

Philip L, Cottrill C, Farrington J, et al. (2017) The digital divide: Patterns, policy and scenarios for connecting the 'final few' in rural communities across Great Britain. *Journal of Rural Studies* 54: 386–398.

Poolsawas S and Napasintuwong O (2013) Farmer innovativeness and hybrid maize diffusion in Thailand. *Journal of International Agricultural and Extension Education* 20: 51–65.

Rotondi V, Stanca L and Tomasuolo M (2017) Connecting alone: Smartphone use, quality of social interactions and well-being. *Journal of Economic Psychology* 63: 17–26.

Rozgonjuk D, Levine JC, Hall BJ, et al. (2018) The association between problematic smartphone use, depression and anxiety symptom severity, and objectively measured smartphone use over one week. *Computers in Human Behavior* 87: 10–17.

Schulz P, Prior J, Kahn L, et al. (2022) Exploring the role of smartphone apps for livestock farmers: Data management, extension and informed decision making. *Journal of Agricultural Education and Extension* 0: 1–22.

Shi J, Chen Z and Tian M (2011) Internet self-efficacy, the need for cognition, and sensation seeking as predictors of problematic use of the internet. *Cyberpsychology, Behavior, and Social Networking* 14: 231–234.

Silver L and Cornibert S (2019) *Smartphone Ownership Is Growing Rapidly Around the World, but Not Always Equally*. USA: Pew Research Center.

Stock JH and Watson MW (2012) *Introduction to econometrics*. Boston: Pearson New York.

Tahamtan I, Pajouhanfar S, Sedghi S, et al. (2017) Factors affecting smartphone adoption for accessing information in medical settings. *Health Information & Libraries Journal* 34: 134–145.

Tamirat TW, Pedersen SM and Lind KM (2018) Farm and operator characteristics affecting adoption of precision agriculture in Denmark and Germany. *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science* 68: 349–357.

Tang L, Luo X, Huang Y, et al. (2023) Can smartphone use increase farmers' willingness to participate in the centralized treatment of rural domestic sewage? Evidence from rural China. *Environment, Development and Sustainability*.

Vahedi Z and Saiphoo A (2018) The association between smartphone use, stress, and anxiety: A meta-analytic review. *Stress and Health* 34: 347–358.

Vellidis G, Liakos V, Andreis JH, et al. (2016) Development and assessment of a smartphone application for irrigation scheduling in cotton. *Computers and Electronics in Agriculture* 127: 249–259.

Walton JC, Lambert DM, Roberts RK, et al. (2008) Adoption and abandonment of precision soil sampling in cotton production. *Journal of Agricultural and Resource Economics*: 428–448.

Wooldridge JM (2010) *Econometric analysis of cross section and panel data*. Cambridge: MIT press.

Zheng H and Ma W (2023) *Smartphone-based information acquisition and wheat farm performance: insights from a doubly robust IPWRA estimator*. *Electronic Commerce Research* 23(2): 633–6588.

About the authors

Wanglin Ma is an Associate Professor of Applied Economics at the Faculty of Agribusiness and Commerce, Lincon University, New Zealand. He obtained his PhD degree from the University of Kiel, Germany. He mainly does research in the fields of agricultural economics and development economics. His research outputs have covered a wide range of topics, such as sustainability and economies of agrifood systems, food production and marketing, farmer organization, agribusiness, rural development, rural-to-urban migration, climate change and adaptation, land transfer, agricultural technology adoption, information technology adoption, welfare and well-being, productivity and efficiency, income growth, farmer subjective well-being, and rural energy transition. He has published over 100 journal articles and also reviewed articles for more than 100 international journals (https://orcid.org/0000-0001-7847-8459). Email: Wanglin.Ma@lincoln.ac.nz.

Enoch Owusu-Sekyere is a researcher at the Department of Economics, SLU. He is a member of the Agricultural and Food Economics group at the Department of Economics, SLU. He is also affiliated with the University of Pretoria and the University of the Free State, South Africa as a guest lecturer and research fellow, respectively. Enoch is an applied and agricultural economist with broad empirical interests and a focus on food systems and their interlinkages with the environment, food security, food policy and sustainable development in developing countries. Email: enoch.owusu.sekyere@slu.se.

Hongyun Zheng is currently an Associate Professor at the College of Economics and Management, Huazhong Agricultural University, Wuhan, China. He works in the field of agricultural economics and rural development. Email: Hongyun.Zheng@outlook.com.

Victor Owusu is a Professor at the Department of Agricultural Economics, Agribusiness and Extension, Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana. He holds a PhD in Development Economics from Vrije Universiteit, Amsterdam, the Netherlands. He has won a number of awards and honours for his research. He has reviewed a number of relevant journals in his field of expertise. Email: vowusu.agric@knust.edu.gh.