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ICT promotes smallholder farmers' perceived self-efficacy and adaptive action to climate change: Empirical research on China's economically developed rural areas

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ABSTRACT

Understanding the impact of technological advancements, such as ICT, on the climate change adaptation actions of smallholder farmers is crucial for comprehending their adaptive strategies. This study utilizes data from a survey of 2230 smallholder farmer households in the developed rural region of the Yangtze River Delta in China to examine the factors influencing their perceived self-efficacy and actions to adapt to climate change. Using binary logit regression and OLS models, we identify the role that determinants of ICT use play in shaping smallholders' perceived self-efficacy and adaptive action. Our findings corroborate that perceived self-efficacy is a robust, positive predictor of adaptive action. The data indicate that the sole presence of adaptation leaders predominantly enhances perceived self-efficacy. In contrast, adaptive investments at the village level are primarily associated with an increase in adaptive actions. However, peer effects may diminish smallholder perceived self-efficacy and adaptive action. In addition, our study indicates that while ICT has not currently supplanted traditional social networks in influencing smallholder climate change adaptation perceived self-efficacy and adaptive action, we cannot dismiss the potential substitution effect. We also clarify why the peer effects of traditional networks have starkly contrasting impacts in developed and less-developed rural regions in China. Overall, our findings underscore the importance of incorporating objective influencing factors of smallholder adaptation actions and their effects on subjective perceived self-efficacy into future climate change adaptation plans and policies to foster adaptation actions.

Introduction

The pervasive ramifications of climate change are becoming increasingly conspicuous, as global warming manifests in more frequent and severe extreme weather events (Swain et al., 2020; van der Geest and Warner, 2020). Particularly vulnerable to the vagaries of such climatic shifts, agricultural systems are grappling with significant consequences (Dardonville et al., 2020; Pais et al., 2020). The diminishing availability of agricultural water resources, driven by climate change, imperils productivity (Tao et al., 2003), with an alarming 40 % of the world's croplands already beset by water scarcity (Liu et al., 2022). Examining China as a case in point, the swelling demand for crop water and heightened potential evapotranspiration due to global warming are anticipated to curtail water resource surpluses by a striking 4 % to 24 % while substantially exacerbating irrigation water requirements during crop growth periods by the 2050 s (Mo et al., 2017). Inextricably linked to food production and farmers' income, climate change accounts for an astounding 60 % of yield variability (Aryal et al., 2020). Disregarding the potential mitigating effects of CO_2 fertilization, projections estimate that crop productivity in China could witness significant declines over the coming decades: wheat yields may plummet by 3–22 %, rice by 8–18 %, and maize by a staggering 9–30 % (Piao et al., 2010; Tao et al., 2008).

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Smallholder farmers in developing nations are particularly susceptible to the detrimental impacts of climate change, including escalated drought frequency and aberrations from customary growing season conditions (Habtemariam et al., 2016; Kotir, 2011; Solaymani, 2018; Tang and Hailu, 2020), such as intensified drought occurrences and deviations from normal growing season conditions (Altieri et al., 2015; Richter and Semenov, 2005). Bolstering their capacity to adapt to climate change is of paramount importance for ensuring national food security and advancing global environmental governance (Wheeler and Von Braun, 2013). In response to these pressing concerns, researchers have increasingly delved into the potential of adaptation as a means to alleviate the consequences of climate change on the lives and livelihoods of smallholder farmers. Recent investigations have concentrated on the theoretical and empirical exploration of the social factors that influence autonomous individual adaptations at multiple levels. The adaptation strategies employed by smallholder farmers must exhibit flexibility and adjustability (Haussmann et al., 2012). Regarded as agents of change, smallholder farmers possess an intimate understanding of the ways in which climate change affects their crop production. They have adeptly adjusted their agricultural practices to curtail the adverse impacts of climate change (Son et al., 2019). For instance, smallholder farmers in China have successfully counteracted 37.9 % of the short-term negative effects of extreme heat exposure on agricultural total factor productivity (Chen and Gong, 2021).

Individual adaptations encompass the adjustments implemented by individuals or smallholder farmers in reaction to stressors or disturbances, or as proactive measures designed to mitigate the impact of future stressors or disturbances (Smit et al., 2000). Conceived as a deliberate and purposeful decision-making process, adaptation can be viewed as comprising several discrete steps or preconditions that pertain to the dissemination and assimilation of information and knowledge within a decision-making system. The comprehension and cognizance of climate change at the individual level are instrumental in enabling adaptive choices (Mertz et al., 2009). Prior research has pinpointed several cognitive factors that could potentially influence adaptive capacity, including geographical location, gender, age, educational background, soil fertility status, access to climate change information, and the availability of credit services (Habtemariam et al., 2016).However, the adaptation efforts undertaken by smallholder farmers may occasionally fall short of the ideal due to inadequate and delayed information on climate change.

The crucial role of ICT in augmenting the effectiveness of smallholder farmers' adaptation strategies to confront the challenges posed by climate change has been widely acknowledged (Antwi-Agyei and Stringer, 2021). Factors such as resource conditions, information channels, cultural quality, and others constrain smallholder farmers' awareness of and response to climate change (Eitzinger et al., 2018; Moerkerken et al., 2020). Increasingly, ICT devices like smartphones, computers, and the internet are employed by households to access climate change information and weather forecasts (Khan et al., 2022a). In numerous contexts, the success of adaptation to climate change will rely on the utilization of ICT to collect and manage necessary information flows (Khan et al., 2022b). The proficiency in utilizing ICT plays a pivotal role in augmenting the adoption of farm-level adaptation strategies (Chetri et al., 2024). Furthermore, there exists substantial potential to refine the efficiency and efficacy of leveraging ICT to bolster the resilience farmers in the face of climate change challenges (Blázquez-Soriano and Ramos-Sandoval, 2022). Research indicates that while ICT can bolster smallholder farmers' access to climate information and heighten their understanding of climate change risks and impacts, the relationship between ICT and self-adaptation is multifaceted and contingent upon various factors (Eakin et al., 2015).

Discerning how smallholder farmers perceive their ability to adapt to climate change is vital in demystifying the process and outcomes of adaptive action. Past studies have scrutinized the determinants that mold smallholder farmers' perceptions of their potential to adapt to climate change and their professed intention to do so. Factors impeding adaptive capacity can be classified into subjective and objective categories (Grothmann and Patt, 2005). On the subjective front, earlier research has delved into material and non-material resources (e.g., ICT), human capital, wealth and financial capital, institutions and rights, and other factors that can simultaneously affect the perception of adaptive capacity and individual intent to adapt to climate change (Burnham and Ma, 2017). Unraveling the ICT factors contributing to low perceptions of adaptive ability may yield valuable insights for planned adaptation interventions, enabling the addressing of these perceived limitations and enhancing the likelihood of successful self-adaptation. However, the impact of the gradual proliferation of ICT on the perceived self-efficacy and adaptive action toward climate change among smallholder farmers in developing countries experiencing rapid economic growth has not been exhaustively examined.

In light of this context, the present study aims to disentangle the effects of ICT on smallholder farmers' perceived self-efficacy and adaptive action, examining them individually. Building upon prior research on climate change adaptation intentions, this investigation delves into how the identified determinants of adaptive capacity shape Chinese smallholder farmers' perceptions of their adaptive capabilities. Moreover, it explores the extent to which perceived self-efficacy translates into actual adaptive action. By examining these relationships, this study aspires to provide a more comprehensive understanding of ICT's role in molding smallholder farmers' climate change adaptation processes and outcomes. Intriguingly, our research also tries to uncovers a significant phenomenon, referred to as the "substitution effect of technology progress", which accentuates the mounting pervasiveness of ICT as a potential force for the gradual displacement of conventional peer effects in steering smallholder farmers' climate change adaptation endeavors.

Theoretical analysis and conceptual framework

Theoretical analysis

Grothmann and Patt (2005) introduced the Model of Private Proactive Adaptation to Climate Change (MPPACC) as a framework to explicate the cognitive determinants affecting an individual's choice to engage in climate change adaptation. This model accentuates the significance of subjective elements, pertaining to an individual's cognitive processes, which hold equal importance as objective factors in ascertaining their adaptive capacity. The appraisal process of adaptation comprises three core components: perceived adaptive efficacy, perceived self-efficacy, and perceived adaptation costs. Of these, perceived self-efficacy plays a pivotal role in molding an individual's perception of their adaptive capacity. The MPPACC framework is grounded in the Protection Motivation Theory (PMT), which has been employed in various health and environmental hazard contexts. During the adaptation appraisal process, individuals assess their ability to prevent harm from the threat and evaluate the costs associated with taking action. This process yields perceived adaptive capacity, which comprises three subcomponents: perceived adaptation efficacy, perceived self-efficacy, and perceived adaptation costs. Based on the outcomes of these processes, individuals may engage in either adaptive or maladaptive action. Adaptive responses lead to adaptation intentions, which may or may not manifest in actual adaptive behavior. Objective adaptive capacity also affects perceived adaptive capacity and determines the realization of adaptation intentions. MPPACC framework offers a valuable foundation for understanding the role of cognitive factors in adaptive action and has been applied to various case studies across different contexts.

Farmers' perceptions of climate change, particularly concerning temperature and precipitation shifts stemming from droughts and floods, are shaped by various factors in economically developed regions of developing countries where ICT is extensively employed. Some farmers discern these changes while others do not, and their adaptation to climate variability is heterogeneous. The drivers underlying their responses may be ascribed to a blend of internal and external factors that influence their adaptation behavior, culminating in intricate decision-making processes. This study aims to enhance the comprehension of farmers' behavior and offer valuable insights to inform policy interventions that bolster farmers' adaptive capacity to climate change.

Zobeidi et al. (2022) executed a thorough review of farmers' incremental adaptation to water scarcity, utilizing MPPACC as a theoretical framework to examine the impact of cognitive determinants on maladaptation in Chinese farmers' responses to water scarcity. (Chenani et al., 2021) furnished an in-depth analysis of individual responses to climate change, employing the MPPACC model as a foundational platform to explore the potential of incremental adaptation in fostering transformative adaptation across diverse scenarios and contexts. (Deuffic et al., 2020) investigated the issue of forest dieback through a systematic review, adapting the MPPACC model to evaluate how forest owners perceive and manage forest dieback as a result of climate change in Germany, France and China.

In this paper, we endeavor to scrutinize the specific factors, particularly ICT, that contribute to an individual's perceived self-efficacy within the MPPACC framework and investigate the relationship between perceived self-efficacy and the adaptive action of smallholder famers in the developed eastern region of China. The MPPACC framework posits that both objective and subjective determinants of adaptive capacity shape an individual's perceived self-efficacy and adaptive action. Identifying which of these determinants exert the most influence on perceived self-efficacy and adaptation intent is vital, as systematically addressing these factors may increase the likelihood of adapting to localized conditions, thereby enhancing smallholder famers' capability to undertake adaptive action autonomously or participate in planned adaptation projects. To accomplish this, we constructed an empirical model, detailed in the methods section, that incorporates a set of factors related to both physical elements (e.g., ICT) and social/institutional elements (e.g., human capital) identified as critical determinants of a system's adaptive capacity (Lemos et al., 2013; Prasad et al., 2009; Saeed et al., 2023).

Previous investigations have delved into the influence of self-efficacy on smallholder farmers' adaptation intentions (Burnham and Ma, 2017). However, it is crucial to acknowledge that adaptation intentions do not invariably translate into tangible adaptive action. Employing the MPPACC framework as a theoretical foundation, the current study aims to investigate the association between perceived self-efficacy and the adaptation behaviors undertaken by smallholder farmers in the economically advanced eastern region of China. While earlier research has predominantly regarded ICT as an integral component of non-material resource variables, a gap in the literature persists concerning the separate exploration of its direct impact on smallholder farmers' perceived self-efficacy and adaptive action. By addressing this lacuna, the present study seeks to enhance our understanding of the nuanced role that ICT plays in shaping the adaptive capacity and actions of smallholder farmers in response to the challenges posed by climate change.

Conceptual framework

In this study, our primary objective is to gain a deeper understanding of the specific factors that affect smallholder farmers' perceived self-efficacy within the MPPACC framework and its relationship with adaptive action, such as adaptive investment, among smallholder famers in the economically developed Yangtze River Delta region. Notably, compared to the existing literature on smallholder famers' climate perception, there is a limited number of studies investigating the influence of modern ICT on smallholder farmers' climate change adaptation in developed rural areas of developing countries.

The MPPACC framework posits that both objective and subjective determinants of adaptive capacity shape an individual's perceived self-efficacy and subsequent adaptive action (Grothmann and Patt, 2005). Identifying the most influential determinants on perceived self-efficacy and adaptation intentions is crucial, as systematically addressing these factors can increase the likelihood of adapting to localized conditions and, in turn, enhance smallholder famers' ability to independently undertake adaptive action. To achieve this, we developed an empirical model (detailed in the methods section) that incorporates a range of factors related to physical elements (e.g., ICT, village investment for households, flood loss, drought losses, farmland area, distance to nearest water infrastructure) and social elements (e.g., education level, presence of village cadre in family), recognized as critical determinants of a system's adaptive capacity.

This study constructs a conceptual framework linking perceived self-efficacy to adaptive action, examining the relationship between adaptive capacity components, such as ICT, human capital, social support, and smallholder farmers' perceived control over their actions. Through this framework, we analyze the impact of objective adaptive capacity on smallholder farmers' perceived self-efficacy and adaptive action (Fig. 1). Specifically, we investigate whether ICT in the economically developed rural areas of the Yangtze River Delta can supplant the peer effects and become the primary factor influencing small farmers' perceived self-efficacy and adaptive action. This examination aims to determine if traditional village social networks (neighbors, relatives, friends) that affect smallholder farmers' responses to climate change are gradually being replaced by modern information acquisition methods, such as ICT, thereby providing contemporary policy support for smallholder farmers in developing countries to address climate change.

Consequently, this study posits the following research hypotheses:

H1: Utilization of information and communication technology (ICT) exerts a positive impact on the perceived self-efficacy of smallholder farmers in adapting to climate change. H2: The impact of ICT on perceived self-efficacy supersedes the influence exerted by peer effects. H3: ICT usage positively correlates with adaptive investment among smallholder farmers in response to climate change. H4: Perceived self-efficacy is positively associated with adaptive investment. H5: The influence of ICT on adaptive investment supersedes the influence exerted by peer effects.

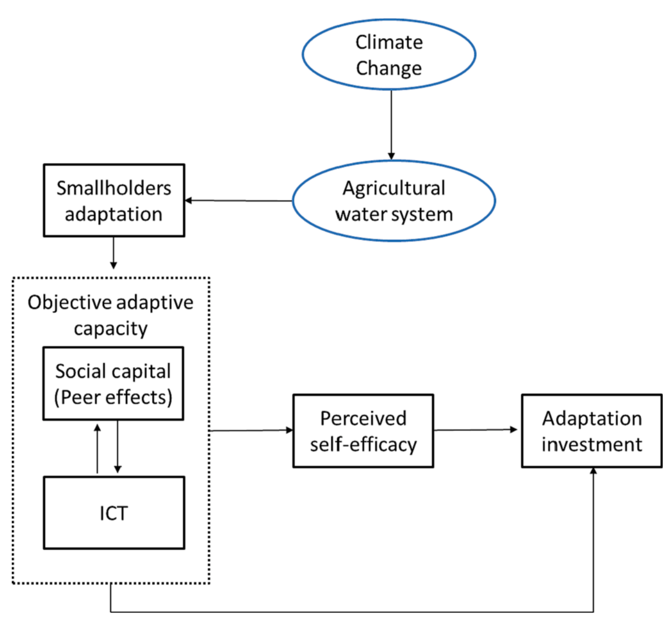

Fig. 1. Conceptual framework.

Study site and methods

Study site

The survey in question was meticulously conducted in Jinhua City, a locale nestled within Zhejiang Province, positioned south of the Yangtze River Delta. Zhejiang Province, renowned for its thriving economy, ranks among China's most developed regions. Positioned along the coastline, this province experiences a heightened sensitivity to climate change impacts among its agricultural communities. Consequently, Zhejiang's agricultural sector serves as a pioneering case study for China in terms of adapting to and mitigating the effects of climate change. Jinhua City resides at the core of Zhejiang Province, its geographical coordinates extending from 119°14′ to 120°46′30″ E longitude and 28°32′ to 29°41′ N latitude. Spanning 129 km north–south and 151 km east–west, the city covers a total land area of 10,942 square kilometers, of which 2,044.7 square kilometers comprise its urban expanse. Jinhua's climate is typified by subtropical monsoonal patterns, rendering it susceptible to frequent typhoon occurrences during summer months. Between 2000 and 2021, the average annual rainfall registered at 1,467.2 mm, with a peak of 2,137.6 mm in 2010 and a trough of 1,045.2 mm in 2003.

Data collection

In this study, we utilize a mixed-methods approach to examine the impact of four variables on smallholder farmers' perceived self-efficacy and investment in climate change adaptation. Our research design combines household surveys with qualitative interviews, offering a comprehensive understanding of the subject matter. Since 2017, we have established a long-term research partnership with eight county-level governments in Jinhua City, conducting semi-structured interviews with agricultural officials and village representatives twice a year to investigate farmer livelihoods.

Before commencing the formal investigation, we consulted local agricultural bureaus in each county government to identify villages where agriculture is a crucial component of livelihoods. Subsequently, we conducted a pretest survey, randomly selecting one village from each of the eight Jinhua counties for further examination and refinement. Given the relatively uniform economic development among Jinhua's rural villages, we chose not to stratify our sample based on economic conditions. Instead, we employed a random sampling technique to select 1–15 villages per town, guided by the town's population size, for our household survey. Data collection occurred simultaneously, with 1,700 trained students serving as survey enumerators under the supervision of professional instructors. Working in groups of three, enumerators maintained an average student-to-teacher ratio of 15.74 and administered four questionnaires per day. Within each village, a fixed proportion of two-thousandths of all towns was sampled using simple random sampling.

In August 2022, our research team completed a survey of 2,230 small farmers across 62 villages in 29 towns and 8 counties within Jinhua City, which is composed of 9 county-level administrative regions (Fig. 2). One region with no rural areas was excluded from the study. The survey aimed to collect information on household socioeconomic characteristics, perceptions of past and future climate change, and implemented adaptation strategies. Furthermore, we investigated the anticipated impacts of future climate change on agriculture and livelihoods, the primary challenges and risks faced by farmers, and the factors influencing farm management decisions.

Firstly, this study deviates from prior research methods that employed regionally diverse selection processes (Burnham et al., 2016; He et al., 2023). Instead, we concentrated on villages within a single city, encompassing all districts of the city, all located within the same climatic zone. This ensures a consistent assessment of climate change impacts, thus reducing potential variability. Secondly, our focus was specifically targeted at the economically advanced region of the Yangtze River Delta in the east. This approach offers valuable insights into the implications of climate change specifically for this developed rural region within a developing country. As economic development and ICT

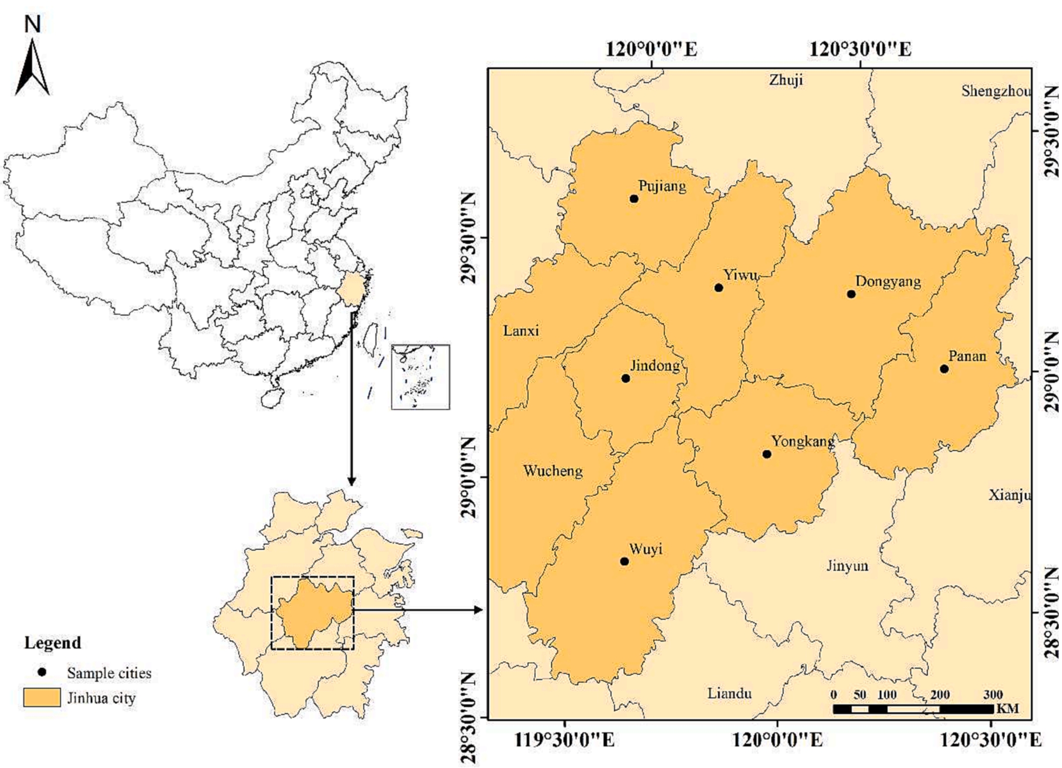

Fig. 2. Map of study area.

penetration continue, such developed rural areas can offer invaluable experiences for less-developed rural areas, thus strengthening the persuasiveness and applicability of our findings. Lastly, the data collection transpired during the lockdown enacted due to the COVID-19 outbreak. This circumstance minimized the influence of off-farm jobs income on farmers' decisions pertaining to climate change adaptive investment. It thus provided a more transparent evaluation of the factors impacting climate change adaptation measures.

Descriptive statistics of main variables

In this study, we designed a survey to evaluate the application of the MPPACC in predicting smallholder farmers' perceived self-efficacy and adaptive investment in response to climate change. The structured, perception-based questionnaire comprised MPPACC constructs, modern and traditional information-gathering methods, and socio-economic variables.

Survey questions were derived from the literature on factors affecting smallholder farmers' perceived self-efficacy and adaptive action in response to climate change (Azadi et al., 2019; Delfiyan et al., 2021; He et al., 2022; Mitter et al., 2019; Schrot et al., 2021; Shi et al., 2019; Zobeidi et al., 2021a; Zobeidi et al., 2022), as well as from reviews of factors influencing households' adaptive action in general (Alam, 2015; Arunrat et al., 2017; Bryan et al., 2013; Dang et al., 2018; Feng et al., 2017; Gessesse et al., 2018; Goli et al., 2020; Nabara et al., 2020; Truelove et al., 2015).

For the dependent variable, perceived self-efficacy (Y1), we assessed smallholder farmers' belief in their ability to adapt effectively to climate change. Respondents indicating belief in their adaptive capacity were assigned a value of 1 ("yes"), while those expressing doubt were assigned a value of 0 ("no"). This binary variable, with 1 denoting self-efficacy belief and 0 indicating its absence, measures farmers' confidence in their adaptive capabilities. The mean value of 0.6401 points to a moderate level of perceived self-efficacy, with a standard deviation of 0.4801, and values ranging from 0 to 1. Regarding adaptive investment (Y2), we queried the extent of smallholder farmers' investment in agricultural water infrastructure over the past three years as a response to climate change. This variable, reflecting investment levels in agricultural water infrastructure, is categorized into six levels based on the amount in Chinese Yuan (CNY), from 0 (no investment) to 6 (over 20,000 CNY). The average investment level is 1.7064, with a standard deviation of 1.0055, indicating variability and a generally low average investment level, ranging from 1 to 6.

The independent variables included: ICT (x1), relatives, friends and neighbors (x2), village adaptive investment for household (x3) and leaders in adaptation (x4). ICT (x1) is a binary variable representing the acquisition of climate change information through Information and Communication Technologies, with 1 indicating usage and 0 non-usage. The mean of 0.3514 suggests limited use among the sample, with a standard deviation of 0.4775, showing variability in ICT use. Our chosen instrumental variable is ICT frequency (IV (ICT)) assesses how frequently farmers obtain climate change information via ICT, on a scale from 1 (infrequently) to 6 (daily). The mean score of 0.5723 indicates relatively infrequent use, with a standard deviation of 1.1744, reflecting significant variability in usage frequency. Relatives, friends and neighbors (x2) is a binary variable measuring the acquisition of climate change adaptation knowledge from social networks. The mean of 0.4823 shows nearly half of the farmers use this source, with a standard deviation of 0.4998, illustrating an even distribution in this practice. Village adaptive investment for household (x3) denotes the level of adaptive investment received from the village for agricultural water infrastructure, scaled similarly to Y2, ranging from 1 (no investment) to 6 (over 20,000 CNY). The mean of 1.6270, with a standard deviation of 0.9972, indicates a generally low investment level from this source. Leaders in adaptation (x4) measures the presence of community leaders in climate change adaptation. This binary variable, with 1 representing leadership presence and 0 its absence, has a mean of 0.6346, suggesting a majority of surveyed communities identify such leaders, and a standard deviation of 0.4816, indicating moderate variation across communities.

Control variables in the study were classified into two primary categories: household characteristics controls and climate change controls. The household characteristics controls include variables such as highest education level (x5), village cadre in household's member (x6), farmland area (x7) and distance to nearest water infrastructure (x8). The climate change controls, conversely, comprise variables associated with losses resulting from climatic disruptions, notably flood loss (x9) and drought losses (x10). Farmers' investment in climate change adaptation may be characterized by lag and discontinuity. To better reflect the long-term trends of smallholder farmers' climate change adaptation and reduce the volatility brought about by uncertainty, we adopted a three-year average adaptive investment amount. Additionally, to account for farmers' climate change-induced losses, we used a three-year average for both drought and flood-related losses.

Highest education level (x5) categorizes the apex education level attained by household members, with a scale from 1 (junior high school or below) to 5 (master's degree or higher). The mean value of 2.5924 suggests that the average highest education level approximates to senior high school or technical school. A standard deviation of 1.2159 indicates significant variability in educational attainment across households, with the range extending from 1 to 5. Village cadre in household member (x6) is a binary variable determining if any household member has occupied a village cadre position within the past three years. The mean value of 0.1273 points to a low incidence of such roles in households, and a standard deviation of 0.3334 suggests minimal variation in this aspect. The variable spans from 0 (no village cadre in the household) to 1 (village cadre present in the household). Farmland area (x7) quantifies the total agricultural land owned by the households, measured in mu. The mean landholding is 6.5140 mu, with a substantial standard deviation of 51.8731, reflecting extensive disparities in land ownership among farmers. The land area varies from 0 to 150 mu. Distance to nearest water infrastructure (x8) gauges the proximity of farmland to the closest irrigation or flood control facilities, rated from 1 (within 100 m) to 5 (more than 1000 m). The mean distance is 2.4146, accompanied by a standard deviation of 1.4004, highlighting diverse farm proximities to water infrastructure, with values ranging from 1 to 5.

Flood loss (x9) assesses the effect of flooding on agricultural output over the previous three years, categorized from 1 (Yield loss above 50 %) to 7 (Yield increase above 50 %). The average impact score is 3.5710 with a standard deviation of 0.8712, indicating a wide spectrum of flood-related agricultural impacts, spanning from 1 to 7. Drought losses (x10), akin to Flood Loss, evaluates the influence of drought on agricultural yields, using the same scale. The mean score stands at 3.6535, with a standard deviation of 0.8188, signifying varied drought impacts on crop yields. This variable's range also extends from 1 to 7. Table 1 displays the definitions and statistics of the variables.

Empirical model

To investigate the influence of factors such as ICT on perceived self-efficacy and adaptative investment, we formulate two distinct models in this study, with a particular focus on probing the potential substitution effect between ICT and the influence of relatives, friends, and neighbors.

Binary logit regression of perceived self-efficacy model

Binary Logit model is constructed to examine the impact of ICT on smallholder farmers' perceived self-efficacy as follows:

$$P(Y=1|X) = \frac{1}{1+\exp\left[-\left(\beta_0+\beta_1x_1+\beta_2x_2+\beta_{12}x_1x_2+\widetilde{X}\widetilde{\beta}\right)\right]} \tag{1}$$

where Y is the binary dependent variable, P (Y = 1|X) denotes probability of perceived self-efficacy = 1. x_1 is ICT, x_2 is relatives, friends,

Table 1
Descriptive Statistics.

Variable	Definition	Mean	SD	Min	Max
Dep.Var.					
Perceived self-efficacy (Y1)	Whether smallholder farmers believe that they can effectively adapt to climate change. (1: Yes; 0: No)	0.6401	0.4801	0	1
Adaptive investment (Y2)	Investment in agricultural water infrastructure to adapt to climate change on their own farm in each of the past 3 years. (CNY in average value of 2019–2021. 1:0; 2:1–2000; 3:2000–5000; 4: 5000–10000; 5:10000–20000; 6: above 20000)	1.7064	1.0055	1	6
Indep.Var.					
ICT (x1)	Whether smallholder farmers obtain information about climate change from ICT. (1: Yes; 0: No)	0.3514	0.4775	0	1
IV (ICT)	The frequency smallholder farmers obtain information about climate change from ICT. (1. Infrequently or with little attention; 2. Monthly; 3. Semi-monthly; 4. Weekly; 5. Every 2–3 days; 6. Daily)	0.5723	1.1744	1	6
Relatives, friends and neighbors (x2)	Whether the smallholder farmers obtain information and knowledge on climate change adaptation from relatives, friends, and neighbors. (1: Yes; 0: No)	0.4823	0.4998	0	1
Village adaptive investment for household (x3)	Smallholder farmers received adaptive investment from the village in agricultural water infrastructure to adapt to climate change. (1:0; 2:1–2000; 3:2000–5000; 4: 5000–10000; 5:10000–20000; 6: above 20000) CNY in average value of 2019–2021.	1.6270	0.9972	1	6
Leaders in Adaptation (x4)	Whether there were leaders who lead adaptive action to climate change. (1: Yes; 0: No)	0.6346	0.4816	0	1
Households' characteristics controls					
Highest education level (x5)	Highest education level of household members. (1: Junior high school or below; 2: Senior high school/technical school; 3: Junior college; 4: Bachelor's degree; 5: Master's degree or above)	2.5924	1.2159	1	5
Village cadre in household's member (*x*6)	Households' members serve as village cadres in the past three years. (1: Yes; 0: No)	0.1273	0.3334	0	1
Farmland area (*x*7)	Households-owned agricultural land area. (mu).	6.5140	51.8731	0	150
Distance to nearest water infrastructure (*x*8)	Distance between the agricultural land and the nearest irrigation, flood control infrastructure. (1: within 100 m; 2: 100–200 m; 3: 200–500 m; 4: 500–1000 m; 5: above 1000) meter in value on interview day.	2.4146	1.4004	1	5
Climate change controls					
Flood loss (*x*9)	Households' agricultural production been affected by floods in each of the past 3 years. (1: Yield loss over 50 %; 2: Yield loss between 20 % and 50 %; 3: Yield loss between 1 % and 20 %; 4: Almost no impact; 5: Yield increase between 1 % and 20 %; 6: Yield increase between 20 % and 50 %; 7: Yield increase over 50 %)	3.5710	0.8712	1	7
Drought losses (x10)	Households' agricultural production been affected by droughts in each of the past 3 years. (1: Yield loss over 50 %; 2: Yield loss between 20 % and 50 %; 3: Yield loss between 1 % and 20 %; 4: Almost no impact; 5: Yield increase between 1 % and 20 %; 6: Yield increase between 20 % and 50 %; 7: Yield increase over 50 %)	3.6535	0.8188	1	7

Notes: During the survey period, 1 $ = 6.1 CNY; 1 mu = 667 m2, or 0.667 ha.

and neighbors, $x_1 x_2$ is the interaction term of ICT and relatives, friends, and neighbors. β_1, β_2 and β_3 are associated coefficients to be estimated. β_0 is intercept term. $\tilde{X}\tilde{\beta}$ denotes the linear combination of other remaining independent variables and coefficients. $\tilde{X}$ includes village adaptive investment for household, leaders in adaptation and other control variables.

OLS regression of adaptive investment model

We employ OLS regression to evaluate the effects of ICT, relatives, friends, and neighbors, perceived self-efficacy and other determinants on farmers' adaptive investment. The model is specified as follows:

$$W = \alpha_0 + X\delta + \varepsilon \quad (2)$$

In equation (2), the dependent variable W is adaptive investment. X

is vector of explanatory variables, including ICT, relatives, friends, and neighbors, interaction term of ICT and relatives, friends, and neighbors, perceived self-efficacy, village adaptive investment for household, leaders in adaptation and other control variables. is constant intercept term. is vector of coefficients to be estimated. refers to error term.

Binary logit regression of perceived self-efficacy 2SLS estimates model

Our study utilizes a two-stage least squares (2SLS) regression model for examining potential endogeneity concerns. The configuration of the model is as follows:

First Stage - Ordinary Least Squares (OLS):

$$IV_{hat} = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_{10} x_{10} + u^* \tag{3}$$

IV_{hat} represents the predicted values of the instrumental variable IV, obtained through an OLS regression on the independent variables x_1 to x_{10}. α_0 to α_{10} are the coefficients estimated in the first stage. u is the error term.

Second Stage - Binary Logit model:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 IV_{hat} + \beta_2 x_2 + \cdots + \beta_{10} x_{10})}} \tag{4}$$

$P(Y = 1|X)$is the probability of the binary dependent variable Y (perceived self-efficacy) being 1. β_0 to β_{10} are the coefficients estimated in the second stage.

Binary IVOLS regression of adaptive investment 2SLS estimates model

First Stage - Ordinary Least Squares (OLS):

Our study utilizes a two-stage least squares (2SLS) regression model for examining potential endogeneity concerns. The configuration of the model is as follows:

First Stage - Ordinary Least Squares (OLS):

$$IV_{hat} = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \cdots + \gamma_{10} x_{10} + v \tag{5}$$

IV_{hat} represents the predicted values of the instrumental variable IV, obtained through an OLS regression on the independent variables x_1 to x_{10}. γ_0 to γ_{10} are the coefficients estimated in the first stage. v is the error term.

Second Stage - Instrumental Variables Ordinary Least Squares (IVOLS):

$$Y = \delta_0 + \delta_1 IV_{hat} + \delta_2 x_2 + \cdots + \delta_{10} x_{10} + \varepsilon \tag{6}$$

Y represents the dependent variable “adaptive investment”. δ_0 to δ_{10} are the coefficients in the second stage. ε is the error term.

Tobit groups regression for robustness model

Tobit model is constructed to examine the impact of ICT on smallholder farmers’ perceived self-efficacy and adaptive investment as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{7}$$

Y could represent perceived self-efficacy or adaptive investment. β_0 to β_{10} are the coefficients of the independent variables. X_1 to X_{10} are the independent variables. ε is the error term.

Results and discussion

Empirical model

As exhibited in Table 2, the gender distribution among the respondents was relatively even, with a minor preponderance of females, who represented 53.29 % of the sample, leaving males to constitute the remaining 46.71 %. The age demographics of the respondents were primarily centered around middle-aged individuals, with those falling within the age range of 46 to 60 years making up 34.78 % of the total. On the other hand, a mere 4.48 % of respondents were under the age of 25. The overrepresentation of middle-aged participants in our survey may be attributed to the fact that the survey was conducted during the COVID-19 lockdown, a period during which the impact of rural–urban migration was mitigated. With respect to educational attainment, a considerable 66.56 % of respondents had acquired an education level equivalent to or below junior high school. In economic terms, a significant 53.03 % of the smallholder famers surveyed operated household farmlands spanning 1–5 mu. Additionally, 28.55 % of respondents declared an annual household income within the range of 50,000 to 99,999 yuan.

Table 2
Household and farm characteristics of smallholder survey respondents.

Household characteristics	Category	Frequency	Proportion
Gender	Male	1042	46.71 %
	Female	1189	53.29 %
Age (year)	< 25	100	4.48 %
	25–35	283	12.68 %
	36–45	323	14.48 %
	46–60	776	34.78 %
	> 60	749	33.57 %
Education (year)	Junior high school or below	1485	66.56 %
	Senior high school/technical school	441	19.77 %
	Junior college	170	7.62 %
	Bachelor’s degree or above	135	6.05 %
Household land (mu)	< 1	781	35.01 %
	1–5	1,183	53.03 %
	> 5	267	11.97 %
Household income (yuan)	< 5000	238	10.67 %
	5000–19999	390	17.48 %
	20000–49999	467	20.93 %
	50000–99999	637	28.55 %
	100000–490000	468	20.98 %
	>500000	31	1.39 %

Notes: During the survey period, 1 $ = 6.1 CNY; 1 mu = 667 m2, or 0.667 ha.

Binary logit of perceived self-efficacy model estimation

The estimation of binary logit models of perceived self-efficacy is presented in Table 3. These models illustrate how smallholder farmers’ perceived self-efficacy in addressing climate change is influenced by factors such as ICT, support from relatives, friends, and neighbors, local investment in households, and the presence of a leader in climate change adaptation. Notably, Models 1 through 4 encompass these core factors, while Models 5 and 6 further scrutinize the potential substitution effect of ICT for peer effects.

Model 1 confirms a substantial positive impact of ICT on perceived self-efficacy amongst smallholder farmers in adapting to climate change, once other variables are controlled for. Notably, the transition from non-ICT to ICT usage results in a perceivable self-efficacy increment of 0.1430, while keeping all other factors constant. This result provides robust empirical support for the proposition that the utilization of ICT may enable smallholder farmers to obtain climate change information more effectively, thereby enhancing their level of perceived self-efficacy.

Conversely, Model 2 indicates that a unit increase in influence from relatives, friends, and neighbors leads to a 2.2481 decrease in the log-odds of perceived self-efficacy, given that all other factors are held constant. This finding is highly significant at the 1 % level, a pattern also noted in other models. One possible explanation for this result is that farmers in developed regions, equipped with some knowledge about addressing climate change, may lack scientific evaluation of adaptation measures, and thus disseminate more negative information, affecting other farmers’ perceived self-efficacy.

All models consistently indicate that the variable ’Village investment for households’ (X3) does not exhibit statistical significance. This implies that its role in augmenting the perceived self-efficacy of

Table 3
Results of binary logit regression of perceived self-efficacy.

Independent variable	Dependent variable: perceived self-efficacy				
	model 1	model 2	model 3	model 4	Model 5
ICT (x1)	0.1430**		0.0330	−0.00379	0.2720
	(0.1000)		(0.111)	(0.1140)	(0.2160)
Relatives, friends and neighbors (x2)		−2.2481***	−2.6640***	−2.4570***	−2.3450***
		(0.1250)	(0.123)	(0.1240)	(0.1520)
X1*X2					−0.3860
					(0.2550)
Village investment for household (x3)	0.0973	0.0760	0.2760		0.0753
	(0.0509)	(0.0585)	(0.0570)		(0.0585)
Leader in adaptation (x4)	1.4260***	1.038***		1.0170***	1.0420***
	(0.0971)	(0.110)		(0.1090)	(0.1100)
Highest education level of family members (x5)	0.0144	−0.0405	−0.0301	−0.0437	−0.0396
	(0.0390)	(0.0441)	(0.0429)	(0.0441)	(0.0442)
Village cadre in family member (*x*6)	−0.2010*	−0.2030	−0.2140*	−0.201	−0.2000
	(0.1130)	(0.1280)	(0.125)	(0.1280)	(0.1280)
Farmland area (*x*7)	0.00376	0.00241	0.00207	0.00227	0.00233
	(0.00246)	(0.00223)	(0.00174)	(0.00214)	(0.00218)
Distance to nearest farmland water infrastructure (*x*8)	0.00765	0.0417	0.02400	0.0370	0.0408
	(0.0337)	(0.0378)	(0.0370)	(0.0376)	(0.0378)
Flood loss (*x*9)	0.0781	0.1930**	0.220***	0.189**	0.1930**
	(0.0683)	(0.0788)	(0.0768)	(0.0787)	(0.0790)
Drought losses (*x*10)	0.0970	0.1380*	0.1280	0.148*	0.1420*
	(0.0730)	(0.0835)	(0.0819)	(0.0832)	(0.0839)
Constant term	0.8300***	0.7830***	1.357***	0.657***	0.6610***
	(0.3450)	(0.4050)	(0.389)	(0.393)	(0.413)
R^2 (Pseudo R2)	0.2946	0.2670	0.2361	0.2664	0.2678
LR chi2	675.73	777.86	687.88	776.18	780.18
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000
Sample size	2230	2230	2230	2230	2230

***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

smallholder farmers in adapting to climate change may be less substantial than previously hypothesized.

Model 4 conveys that the presence of a leader in adaptation is associated with a significant increase of 1.0170 in the log-odds of perceived self-efficacy, again assuming all other factors constant. This result is highly significant at the 1 % level and aligns with empirical observations. Similar significant outcomes have been observed in other models. Particularly in rural Chinese communities, the presence of a leader, especially a village official or elite, significantly enhances farmers' perceived self-efficacy in responding to climate change.

In model 3 and 4, the simultaneous presence of ICT (X1) and peer effects from relatives, friends, and neighbors (X2) results in opposite signs, with only X2 being significant. This may suggest a potential substitution effect of technology on peer effects. Accordingly, an interaction term was introduced to construct Model 5. However, the interaction term X1*X2 in Model 5 is not statistically significant, implying no notable interaction effect between ICT and peer effects on perceived self-efficacy. This absence of significance does not necessarily nullify the substitution effect of technological progression on traditional peer effects. The interpretation from Models 5 suggests that in the developed rural areas of China, ICT has started to exert a positive influence on smallholder farmers' perceived self-efficacy in climate change adaptation, yet it does not replace the peer effects and impact of traditional rural social networks. Contrary to previous research, our study identifies the prominent role of ICT, especially in developing nations and more affluent regions. As ICT advances and becomes more prevalent, it is progressively emerging as a crucial determinant of farmers' perceived self-efficacy.

Regarding control variables, village cadre in family member (x6): Presence of a village cadre in the family is consistently associated with a statistically significant decrease in perceived self-efficacy across all models. farmland area (x7): Across all models, an increase in the farmland area is significantly linked to a slight increase in perceived self-efficacy. flood loss (x9): Increase in flood loss is significantly associated with an increase in perceived self-efficacy in Models 2, 3, 4, and 5. Increase in drought losses (x10) is significantly associated with an increase in perceived self-efficacy in Models 2, 4, and 5. The effect of highest education level of family members (x5), distance to nearest farmland water infrastructure (x8): on self-efficacy non-significant across the models.

OLS of adaptive investment model estimation

Table 4 displays the OLS models' estimation for adaptive investment, elucidating the factors affecting smallholder farmers' investment towards climate change adaptation. These influences span across ICT, support from relatives, friends, and neighbors, village-level investment for households, the leadership in climate change adaptation and perceived self-efficacy. Models 6 through 9, along with model 11, incorporate these core determinants. Conversely, Models 10 delve deeper, probing the potential substitution effect of ICT for peer effects.

Model 6 delineates a positive and statistically significant relationship between ICT and adaptive investment, suggesting that a unit increase in ICT corresponds with a 6.76 % uptick in adaptive investment. A notable barrier to successful adaptive investment among smallholder farmers is the absence of climate change and meteorological information (Chenani et al., 2021; Pandey et al., 2018). Our research provides empirical evidence indicating that the extensive deployment of ICT helps overcome this obstacle, subsequently promoting an increase in climate change adaptive investment among smallholder farmers.

Model 7–11 unveils a negative and highly significant association between peer effects and adaptive investment. This finding challenges the prevailing conclusion that peer effects invariably foster positive impacts on farmers' climate change adaptation. The significant negative correlation may be due to farmers in more developed regions already possessing substantial climate change knowledge. Information from neighbors and relatives might be subjectively biased and unscientific, inadvertently impeding proper climate change responses. Our findings comprehensively illuminate the dual effects of peer effects across different regions, further highlighting the relative advantages of ICT in

Table 4
Results of OLS regression of adaptive investment.

Independent variable	Dependent variable: Adaptive investment					
	model 6	model 7	model 8	model 9	Model 10	Model 11
ICT (x1)	0.0676***		0.0510	0.0560	0.0566	0.0524
	(0.0393)		(0.0391)	(0.0430)	(0.0547)	(0.0391)
Relatives, friends and neighbors (x2)		−0.2490***	−0.2310***	−0.3710***	−0.2430***	−0.2490***
		(0.0397)	(0.0382)	(0.0433)	(0.0485)	(0.0450)
X1*X2					−0.0086	
					(0.0779)	
Village investment for household (x3)	0.4350***	0.4180***	0.4140***		0.4180***	0.4180***
	(0.0193)	(0.0194)	(0.0192)		(0.0194)	(0.0194)
Leader in adaptation (x4)	0.0210	−0.0502		0.0759*	−0.0516	−0.0501
	(0.0398)	(0.0412)		(0.0448)	(0.0412)	(0.0422
Perceived self-efficacy						−0.00831***
						(0.0466)
Highest education level of family members (x5)	0.00121	−0.00250	−0.00410	0.0111	−0.00369	−0.00377
	(0.0155)	(0.0153)	(0.0154)	(0.0169)	(0.0154)	(0.0154)
Village cadre in family member (*x*6)	−0.0467	−0.0398	−0.0396	−0.0471	−0.0410	−0.0414
	(0.0440)	(0.0436)	(0.0436)	(0.0480)	(0.0436)	(0.0437)
Farmland area (*x*7)	0.000673*	0.000680*	0.000686*	0.00104***	0.000692*	0.000695*
	(0.000361)	(0.000358)	(0.000358)	(0.000394)	(0.000358)	(0.000359)
Distance to nearest water infrastructure (*x*8)	0.0435***	0.0476***	0.0480***	0.0729***	0.0469***	0.0470***
	(0.0134)	(0.0133)	(0.0133)	(0.0146)	(0.0133)	(0.0133)
Flood loss (*x*9)	−0.1150***	−0.1070***	−0.1090***	−0.0943***	−0.1080***	−0.1070***
	(0.0272)	(0.0270)	(0.0269)	(0.0297)	(0.0270)	(0.0270)
Drought losses (*x*10)	−0.0864***	−0.0876***	−0.0861***	−0.1450***	−0.0860***	−0.0858***
	(0.0290)	(0.0288)	(0.0288)	(0.0315)	(0.0288)	(0.0288)
Constant term	1.6580***	1.8450***	1.8000***	2.5670***	1.8290***	1.837***
	(0.1370)	(0.138)	(0.136)	(0.148)	(0.1400)	(0.142)
$R^2$2 (Pseudo R2)	0.2344	0.2467	0.2468	0.0894	0.2473	0.2473
F (Quasi—LR)	75.51	80.77	80.80	24.21	66.24	66.25
Pro (F/Quasi—LR)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sample size	2230	2230	2230	2230	2230	2230

***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

terms of its scientific basis and controllability. Our research verifies the heterogeneous impacts of peer effects on smallholder farmers' climate change adaptation behaviors across different regions.

Considering that the variable X3 (village investment for households) maintains statistical significance across all models incorporating X3 in our analysis, it indicates a consistent and substantial impact of village investment on the adaptive investment behaviors of smallholder farmers. Our findings show that public or governmental climate change adaptive investment would not replace smallholder farmers' adaptive investment. Contrarily, we find that in situations with public investment, farmers reciprocally enhance their household investment, thus augmenting the results of climate change adaptation efforts. The variable X4, denoted as "Leader in adaptation," exhibits an effect on adaptive investment that is generally not significant, indicating its potentially ambiguous impact in this specific context.

Model 8 to model 10 scrutinize the substitution effect between X1 (ICT) and X2 (Relatives, friends and neighbors) by including an interaction term (X1*X2). In both models, the coefficients for ICT and peer influence are respectively positive and negative. Yet, the interaction term in model 10 is insignificant, indicating no considerable substitution effect between ICT and peer influence regarding adaptive investment. Although ICT, under current rural development conditions and variable settings, cannot yet replace the influence of peer effects on smallholder adaptive investment, this does not preclude the potential substitution effect of ICT for peer effects in other scenarios. We can even hypothesize that as traditional social networks diminish and ICT becomes more prevalent, ICT may potentially substitute for peer effects in the future.

Model 11 includes perceived self-efficacy, a variable demonstrating a significant positive correlation with adaptive investment. This suggests that confidence in one's ability to adapt to climate change significantly boosts adaptive investment, further corroborating previous studies where self-efficacy is recognized as a crucial predictor of adaptive behavior (Pakmehr et al., 2020; Zobeidi et al., 2021b).

For the control variables, an increase in farmland area (X7) is invariably linked to a slight elevation in adaptive investment, indicating that larger farms might be more equipped or motivated to invest in adaptation measures. Distance to the nearest water infrastructure (X8) also exhibits a significant positive association with adaptive investment, suggesting that improved access to water resources might incentivize adaptation efforts. The observed negative correlation between flood loss (X9) and drought losses (X10) with adaptive investment suggests a trend where increased losses from floods and droughts are associated with a decline in smallholder farmers' investment in adaptive measures. This trend could be indicative of the economic constraints imposed by these losses, which limit farmers' ability to invest in adaptation strategies. Alternatively, this pattern might reflect a scenario where recurrent losses lead to a reduced perception of the effectiveness or value of such investments, potentially due to heightened uncertainty or unpredictability in the context of ongoing environmental challenges. This finding underscores the necessity for an in-depth investigation into the impediments smallholder farmers encounter in adapting to climate-induced adversities. However, a village cadre in the family, the influences of the highest education level among family members remain insignificant across the models, signaling that these factors do not strongly impact adaptive investment.

Causal identification issues and robustness tests

Causal identification issues

In examining the exclusion restriction criteria for our selected IV the frequency of obtaining climate change information via ICT contemporary research delineates the indirect nexus between the IV and the dependent variables, namely perceived self-efficacy and adaptive investment. Self-efficacy is forged by an amalgam of personal, social, and informational elements, extending beyond mere exposure to information (Bandura, 1977; Bandura, 1993). The impact of ICT-mediated information on behavioral intentions, revealing this impact as moderated by attitudes and perceived control, via intricate cognitive processes

(Wang et al., 2020).Engagement with climate change information exhibits individual variability, contingent on cultural, psychological, and socio-political milieus (Smith and Joffe, 2013). Furthermore, Moser and Ekstrom (2010) demonstrate that responses to climate change in terms of adaptation behaviors are sculpted by a confluence of information exposure, socio-economic conditions, and institutional structures. Collectively, these studies fortify the understanding that the influence of our chosen IV on the dependent variables is mediated through several indirect channels, thereby corroborating the appropriateness of our IV selection in line with exclusion restriction criteria.

To further corroborate these findings, we employed instrumental variables to examine endogeneity concerns. The selected instrument was the frequency of obtaining climate change information through ICT (IV). We performed a weak instrument test and an over-identification test to verify the validity of our chosen IV. The weak instrument test results indicate that the F-statistic is 1741.23, with a p-value less than 0.0001. This F-statistic significantly exceeds critical values, suggesting our IV, is robust and suitable for our IV regression. Regarding the over-identification test, we used a single instrument for one endogenous variable, thus eliminating the need for this test. In such a case, the model is deemed to be exactly identified, and the chosen instrument can be considered apt. These results collectively validate the utility of our chosen instrument in the IV regression analysis.

Concerning perceived self-efficacy and ICT, we applied the two-stage least squares (2SLS) IV regression methodology to examine potential endogeneity issues. Table 5 displays the results of the binary logit regression of perceived self-efficacy and 2SLS estimates taking potential endogeneity into account. The first stage of the analysis incorporated a linear regression model, with ICT regressed on the IV and other variables (X2, X3, X4, X6, X7 and X10). In the second stage, we utilized a logistic regression model with the dependent variable perceived self-efficacy regressed on the predicted values of ICT_hat and control variables.

The first-stage results revealed that the IV was statistically significant (Coef. = 0.268, p-value = 0.00642), affirming the relevance of our selected instrument. The F-statistic for the first-stage model was 178.46, exceeding the conventional threshold of 10, confirming that our instrument is robust. In the second-stage logistic regression results where the predicted values of ICT (ICT_hat) derived from the first stage are included in the model, the coefficient of the variable ICT (x1) hat was not statistically significant (Coef. = -0.153, p-value = 0.1680), suggesting that there is no compelling evidence of endogeneity in our model. The other covariates exhibited varying degrees of significance, with some demonstrating a statistically significant relationship with the dependent variable. In conclusion, our two-stage IV regression analysis suggests that the endogeneity concerns in our model are not substantial, and the selected IV appears to be valid and robust.

Subsequently, we addressed potential endogeneity issues associated with ICT and adaptive investment. From a practical standpoint, these two variables could potentially be endogenous as small farmers might increase their ICT use in response to an increase in adaptive investment to ensure its effectiveness.

To assess these potential endogeneity issues within the OLS regression of adaptive investment, Wooldridge's test method was employed in this study. The evidence from the Durbin and Wu-Hausman tests, yielding p-values of 0.4904 and 0.4913 respectively, suggested no significant endogeneity. Standard statistical criteria assert that a p-value below 0.05 provides a basis for rejecting the null hypothesis of no endogeneity. Considering the obtained p-values, there isn't sufficient evidence to reject this null hypothesis, which implies that endogeneity may not be a significant issue in the OLS regression analysis for adaptive investment. This result confers a degree of confidence in the validity of the OLS regression model utilized in this study.

Further, to rigorously probe potential endogeneity issues between adaptive investment and ICT, an Instrumental Variable (IV) approach was adopted (refer to Table 6). Given the continuous nature of both the dependent variable Y2 and the IV, the binary variable X2 was

Table 5
Results of binary logit regression of perceived self-efficacy 2SLS estimates.

Independent variable	First-stage OLS ICT	Second-stage Logit ICT_hat Perceived self-efficacy (Y1)
IV (ICT)	0.2680*** (0.00642)	
ICT (x1) hat		−0.1530 (0.1680)
Relatives, friends and neighbors (x2)	−0.0528*** (0.0162)	−2.4810*** (0.1250)
Village adaptive investment for household (x3)	−0.00205 (0.00788)	−0.0745 (0.0586)
Leaders in Adaptation (x4)	0.0329* (0.0168)	1.0440*** (0.1110)
Highest education level of family members (x5)	0.0174*** (0.00625)	−0.0335 (0.0443)
Village cadre in household's member (x6)	0.0268 (0.0228)	−0.0763 (0.170)
Farmland area (x7)	−9.96e-05 (0.000146)	0.00239 (0.00216)
Distance to nearest water infrastructure (x8)	0.0101* (0.00542)	0.0426 (0.0378)
Flood loss (x9)	0.0148 (0.0110)	0.193** (0.0789)
Drought losses (x10)	−0.0236** (0.0117)	0.134 (0.0837)
Constant term	0.172** (0.0690)	3.091*** (0.502)
$R^2$2 (Pseudo R2)	0.4458	0.26650
F (Quasi—LR)	178.46	
Pro (F/Quasi—LR)	0.0000	0.0000
Sample size	2230	2230

***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Table 6
Results of binary IVOLS regression of adaptive investment 2SLS estimates.

Independent variable	OLS Dependent variable: Adaptive investment (Y2)	IVOLS 2sls Dependent variable: Adaptive investment (Y2)
ICT (x1)_dummy1	−0.0527 (0.0391)	−0.0527 (0.0390)
ICT (x1)_dummy2		
Relatives, friends and neighbors (x2)	−0.2470*** (0.0450)	−0.2470*** (0.0449)
Village investment for household (x3)	0.4170*** (0.0194)	0.4170*** (0.0193)
Leader in Adaptation (x4)	−0.0526 (0.0422)	−0.0526 (0.0421)
Perceived self-efficacy	−0.0075 (0.0466)	−0.0075 (0.0464)
Highest education level (x5)	−0.0046 (0.0154)	−0.0046 (0.0153)
Village cadre in family member (x6)	−0.0781 (0.0562)	−0.0781 (0.0560)
Farmland area (x7)	0.00072** (0.00036)	0.00072** (0.00036)
Distance to nearest water infrastructure (x8)	0.0464*** (0.0133)	0.0464*** (0.0133)
flood loss (x9)	−0.1060*** (0.0271)	−0.1060*** (0.0270)
drought losses (x10)	−0.0876*** (0.0288)	−0.0876*** (0.0287)
Constant term	2.2160*** (0.1790)	2.2160*** (0.1780)
$R^2$2 (Pseudo R2)	0.2476	0.2578
F (Quasi—LR)	66.37	
Pro (F/Quasi—LR)	0.0000	0.0000
Sample size	2230	2230

***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

transformed into two dummy variables: X2_dummy1 and X2_dummy2. Subsequently, the Two-Stage Least Squares (2SLS) technique and the Hausman test were used to evaluate potential endogeneity and validate the robustness of our primary regression results.

Initially, an OLS regression was performed with Y1 as the dependent variable and X2_dummy1 and X2_dummy2 as predictors, alongside all control variables. To address potential endogeneity, the 2SLS method was implemented, using the interaction term X1X2 as an instrument for X2_dummy1 and X2_dummy2. In this regression, only one dummy variable (e.g., X2_dummy1) needed to be included, as X2 is a categorical variable with binary values. The 2SLS results indicated a non-significant relationship between X2_dummy1 and Y1, with a negative coefficient of −0.0527 ($p = 0.177$).

To evaluate the consistency of the estimations derived from both the OLS and 2SLS methods, a Hausman test was conducted. The null hypothesis posits no systematic difference between the IV and OLS estimators. The test statistic was chi2 (10) = 3.64, with a p-value of 0.9621. Given this high p-value, we cannot reject the null hypothesis, suggesting that endogeneity may not pose a significant concern in our model.

Robustness tests

In our robustness checks, we employed an alternative sample selection approach and focused on two sets of models. For Models 12 and 14, we excluded observations with postgraduate and higher education levels, retaining only those with undergraduate and lower education levels. This decision was made to mitigate potential correlations between higher education levels and ICT adoption. Subsequently, we examined the robustness of the relationship between ICT usage and perceived self-efficacy, as well as the association between ICT usage and adaptive investment.

For Models 2 and 4, we removed observations from households with village cadres, as these individuals might be more inclined to adopt ICT due to their work requirements, which include utilizing ICT to access climate change information. Our modified sample thus comprised solely non-cadre households. We proceeded to assess the robustness of the relationship between ICT usage and perceived self-efficacy, as well as the association between ICT usage and adaptive investment in this alternative sample.

By implementing these alternative sample selection methods, our objective was to offer a comprehensive evaluation of the robustness of our principal findings, ensuring that the observed relationships were not driven by potential biases arising from specific sample characteristics. As demonstrated in Table 7, our robustness checks were successful in validating the initial results. For the remaining key variables—Neighbors (x2), Village Investment for Household (x3), and Leader in Adaptation (x4)—we employed the same method to construct respective models for robustness testing. The results from these tests all satisfied the required robustness criteria. Owing to constraints in space, we do not present these results herein.

Table 7
Groups regression results of tobit model for robustness test.

Independent variable	Sample excludes graduate degree or above Model 12 perceived self-efficacy (Y1)	Sample excludes households with village cadres Model 13 perceived self-efficacy (Y1)	Sample excludes graduate degree or above Model 14 Adaptive investment (Y2)	Sample excludes households with village cadres Model 15 Adaptive investment (Y2)
ICT (x1)	0.1880** (0.0949)	0.2260** (0.1000)	0.0843* (0.0440)	0.104** (0.0459)
Highest education level of family members (x5)		0.0466 (0.0387)		0.0258 (0.0180)
Village cadre in family member (x6)	−0.438*** (0.144)		−0.203*** (0.0638)	
Farmland area (x7)	0.00496* (0.00282)	0.00561* (0.00314)	0.00111*** (0.000401)	0.00115*** (0.000399)
Distance to nearest farmland water infrastructure (x8)	−0.0185 (0.0322)	−0.00519 (0.0337)	0.0652*** (0.0151)	0.0623*** (0.0156)
Flood loss (x9)	0.127* (0.0654)	0.126* (0.0699)	−0.104*** (0.0306)	−0.0849*** (0.0324)
Drought losses (x10)	0.0393 (0.0690)	0.0276 (0.0744)	−0.148*** (0.0323)	−0.165*** (0.0346)
Constant term	0.757** (0.354)	−0.240*** (0.2650)	2.807*** (0.1610)	2.326*** (0.125)
R^2 (Pseudo R2)	0.2599	0.2037	0.2541	0.2514
LR chi2	282	27.83		
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Sample size	2,163	1,947	2,163	1,947

***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Discussion

This study utilized data from 2,230 farmers in 2022, employing binary logit and OLS models to analyze the influence of ICT - as representative of technological advancement - on traditional social networks in China, with a specific focus on the effects on smallholder farmers' perceived self-efficacy and climate change adaptive investment. The findings confirm the validity of Hypotheses 1, 3, and 4, while Hypotheses 2 and 5 are not supported: H1: The deployment of ICT positively influences the perceived self-efficacy of smallholder farmers in their adaptation to climate change. H2: The effect of ICT on perceived self-efficacy does not surpass the influence of peer effects. H3: There is a positive relationship between ICT usage and adaptive investment among smallholder farmers addressing climate change. H4: A positive correlation exists between perceived self-efficacy and adaptive investment. H5: The impact of ICT on adaptive investment does not replace the influence of peer effects.

This study offers noteworthy advancements in the field in the following ways: Firstly, this study, grounded on field survey data, selected rural regions in the developed Yangtze River Delta of China. We observed negative peer effects on smallholder farmers' perceived self-efficacy and adaptive investment in these developed rural areas of China. Additionally, we noted heterogeneity in these effects between developed and underdeveloped rural regions. Secondly, this study expands existing literature by examining the impact of ICT on the perceived self-efficacy and adaptive investment of smallholder farmers in developed rural areas of China in response to climate change. Thirdly, our findings validate previous research within the MAPPC framework, confirming that a smallholder's perceived self-efficacy is a crucial determinant of their adaptive investment in response to climate change. Finally, we reveal a potential substitutive effect of ICT-led technological advancement on traditional rural social networks during the process of smallholder climate change adaptation.

The academic community has conducted in-depth research on smallholder famers' adaptation to climate change, with some scholars focusing on motivations for adaptation. Currently, some researchers are interested in the role of ICT in smallholder famers' adaptation to climate change. However, few have explored the different roles that traditional social peer effects play in climate change adaptation among smallholder famers in underdeveloped and developed rural areas. Further, the potential substitutive effects of ICT-led technological advancement on traditional social peer effects in climate change perceived self-efficacy and adaptive action have been largely unexplored.

Our results generally support the findings of earlier studies examining the cognitive dimensions of climate change adaptation. Specifically, our findings offer robust empirical evidence supporting the hypothesis that an individual's perceived self-efficacy plays a pivotal role in their adaptive action (Grothmann and Patt, 2005). However, our research challenges some previous studies' conclusions. Contrary to earlier research conducted in underdeveloped rural areas, we found that peer effects do not positively influence adaptive investment in developed rural areas. Instead, these peer effects were negative, thereby promoting a more comprehensive understanding of peer effects' heterogeneity on perceived self-efficacy and adaptive action across rural areas of different economic development levels.

Concerning factors influencing perceived self-efficacy, in addition to past experiences, our results suggest that the use of ICT may enhance perceived self-efficacy by mediating the impacts of climate change on smallholder farmers' efficiency and content of information acquisition. Intriguingly, our conclusions suggest that peer effects, involving relationships with relatives, friends and neighbors may potentially diminish levels of perceived self-efficacy. One possible explanation is that individual perceived self-efficacy might be more significantly influenced by prior experiences handling climatic stressors, rather than by an understanding of the future potential impacts of climate (Kuruppu and Liverman, 2011). In the economically advanced rural areas of the Yangtze River Delta, smallholder famers are already equipped with some knowledge of adapting to climate change. Consequently, these farmers require more systematic and scientific knowledge to enhance their adaptive capacities against climate change. Traditional social networks often disseminate subjective experiences of climate change, which, when compared to ICT, could lack a systematic and scientific nature. This discrepancy may negatively influence the perceived self-efficacy among these farmers.

Our research delineates the differential effects of specific variables on smallholder farmers' responses to climate change, as evidenced by contrasting data from Tables 3 and 4. The provision of village investment for climate change (X3) is observed to escalate adaptive investment but does not correspondingly augment farmers' perceived self-efficacy. This suggests that financial backing facilitates adaptation actions, it does inherently enhance farmers' assurance in their capacity to tackle climate-related challenges. In contrast, occupying a leadership role in adaptation (X4) significantly elevates perceived self-efficacy among farmers, yet it does not markedly influence their adaptive investment. This finding highlights the pivotal role of leadership and psychological empowerment in bolstering farmers' confidence, though it does not directly result in heightened adaptation activities. These findings emphasize the intricate interplay between external assistance and internal psychological factors in shaping climate change adaptation strategies among smallholder farmers. This outcome both deepens and amends previous research findings, which indicated that village investment for households significantly increases smallholder famers' perceived self-efficacy (Duffy et al., 2020). Although the use of ICT may contribute to higher levels of perceived self-efficacy, it currently cannot substitute the peer effects. However, we cannot rule out the possibility that, with future advancements in ICT, coupled with further modernization of rural society, the ongoing urbanization and resultant dissolution of traditional rural social networks may lead to an emergence of substitutive effects of ICT on peer effects.

Regarding the factors influencing adaptive action, our study further underscores the role of ICT in enhancing adaptive investment, consistent with previous research (Khan et al., 2022a, Khan et al., 2022b). More specifically, given a certain level of knowledge about climate change amongst smallholder famers in developed rural areas of Yangtze River Delta, they require more advanced and relevant knowledge and information of climate change. With the Chinese government increasingly prioritizing climate change, vast amounts of information are released by meteorological departments. Smallholder famers can obtain this knowledge and information at a low cost through ICT, bolstering their adaptive investment.

We found that peer effects, namely influence from relatives, friends, and neighbors, have a negative impact on adaptive investment. This result contrasts with previous research conducted in less developed rural areas of Southwest China (Ma et al., 2022). This disparity can help explain the heterogeneous role of traditional social networks in climate change adaptive action among smallholder famers in developed and less developed rural areas. The discernible disparity in rural per capita disposable income, amounting to 16,958 yuan between Jinhua city (35,630 yuan) and Sichuan province (18,672 yuan) in 2022. In less developed regions, exemplified by rural Sichuan, smallholder farmers exhibit a greater reliance on traditional social networks for information and support. In less developed regions, smallholder farmers exhibit a greater reliance on traditional social networks for information and support, smallholder famers have limited climate change knowledge and scant opportunities to access information via ICT, causing subjective information obtained from relatives, friends, and neighbors to be more prominent and positively influence climate change adaptive investment. In contrast, in developed rural areas where smallholder famers already have a certain level of climate change knowledge, the limited and subjective information from relatives, friends, and neighbors can hinder adaptive investment. This highlights the criticality of socioeconomic characteristics in assessing the generalizability of our research findings. We incorporated an interaction term between ICT and relatives, friends, and neighbors in our model to examine their potential substitution effects. Although using ICT might significantly enhance smallholder famers' adaptive investment, it currently cannot replace the peer effects from traditional social networks. Nonetheless, we cannot discount the possibility of ICT progressively substituting traditional social networks in smallholder famers' climate change adaptive investment due to ICT advancements.

Our findings affirm that village investment positively impacts the adaptive investment of smallholder famers. The adaptive investment of smallholder famers and public adaptive investment complement each other, with public investment stimulating the adaptive investment of smallholder famers. Contrary to prior research suggesting that smallholder famers would rely on governmental adaptive investment, thereby reducing their own (Burnham and Ma, 2017), our results indicate that smallholder famers do not solely depend on public funding for adaptive investment. Within the framework of MPPACC, our conclusions provide empirical evidence supporting previous studies, which identified perceived self-efficacy as a key predictor of adaptive action (Bechtoldt et al., 2020; Zobeidi et al., 2022).

Conclusions and policy implications

The primary contribution of this paper is crucially the elucidation of the differential impacts of peer effects in rural China, varying by the level of regional development. Unlike in less developed rural areas, peer effects in more developed rural regions negatively influence smallholder farmers' responses to climate change. Significantly, peer effects are not replaced by the application of technological advancements like ICT. This understanding aids in comprehending the diverse influences of peer effects within the varied developmental contexts of rural China.

Moreover, our study enhances understanding of the cognitive and action-oriented dimensions of perceived self-efficacy and adaptive action, as conceptualized in the framework MPPACC (Grothmann & Patt, 2005). We systematically scrutinized how various subjective and objective factors, potentially bolstering or hindering adaptation, shape smallholders' perceived self-efficacy and their consequent adaptive action. Corroborating recent research (Zobeidi et al., 2022; Bechtoldt et al., 2020), our study reinforces the notion that perceived self-efficacy are potent, positive predictors of adaptive action. Additionally, our results suggest that the presence of adaptation leaders solely contributes to an increase in perceived self-efficacy. Conversely, village adaptive investment for households only fosters adaptive actions, whereas the utilization of ICT can enhance both. Lastly, our research underscores the significance of considering the differential impacts of peer effects across varied economic development stages when analyzing climate change adaptation in rural areas. While the current findings suggest that ICT is not an outright substitute for traditional social networks, the role of ICT could evolve with technological advancements and shifting social contexts. These results underscore the imperative of ongoing surveillance and research into the dynamic interplay between technological progress, social factors, and the evolution of climate change adaptation strategies among smallholders.

This research provides policy implications for directing stallholder farmers in their responses to climate change. Initially, we advocate for the establishment of a national climate change ICT center, encompassing two primary components: a climate change information release system and an extreme weather Warning System. The creation of this center would facilitate a gradual shift in farmers' acquisition of climate change information through ICT, fostering a substitution effect where technological advancements supplant traditional social network channels for information dissemination. Access to timely and accurate information via ICT is projected to significantly improve the efficiency and effectiveness of climate change response strategies. Subsequently, our research reveals that village investment dedicated to climate change notably increases farmers' adaptive investment. In contrast, assuming a leadership role in adaptation substantially boosts farmers' perceived self-efficacy, but does not significantly affect their adaptive investment. This finding suggests a crucial need for a policy shift, redirecting the focus from primarily supporting leaders in adaptation to prioritizing village adaptive investment, moving away from the current policy's focus on the leadership role of village cadres and other rural elites. Such a policy realignment is critical for equipping smallholder farmers with the resources necessary to adopt more proactive and efficacious strategies to address the challenges posed by climate change.

This article proposes a prospective research direction exploring how AI integrated with ICT can refine the precision and relevance of weather information and improve climate adaptation strategies for smallholder farmers across regions with varying socioeconomic structures.

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CRediT authorship contribution statement

Yu Yang: Conceptualization, Data curation, Methodology, Writing – original draft, Writing – review & editing. **Yang Zhang:** Software, Visualization. **Benz Xinqi Zhu:** Conceptualization, Data curation. **Jiajun Zhou:** Methodology, Software. **Yang Liu:** Software, Visualization. **Dongxia Gao:** Funding acquisition, Investigation. **Johannes Sauer:** Supervision, Writing – review & editing.

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

Data will be made available on request.

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