sustainability

MDPI

Article

Digital Technologies Adoption and Economic Benefits in Agriculture: A Mixed-Methods Approach

Wenxuan Geng †, Liping Liu †, Junye Zhao *, Xiaoru Kang and Wenliang Wang

Agricultural Information Institute, Chinese Academy of Agricultural Sciences, No. 12 Zhongguancun South St., Beijing 100081, China; wenxuangeng@163.com (W.G.); liuliping980707@163.com (L.L.); kangxiaoru00@163.com (X.K.); wwl_work_1998@163.com (W.W.)

* Correspondence: zhaojunye@caas.cn; Tel.: +86-10-82105209

† These authors contributed equally to this work.

Abstract: Governments globally aim to boost productivity and enhance farmers' livelihoods, addressing challenges like climate change, food security, and labor shortages through digital technologies. However, adoption rates in developing countries remain low due to uncertainties regarding expected returns and obstacles stemming from subjective and objective factors among farmers. This study takes China as a case study to examine the internal and external factors influencing growers' adoption intensity of digital technology and its impact on enhancing economic benefits, aiming to provide valuable insights for the promotion of digital technology in other countries and regions. This study employs a mixed-methods approach, integrating qualitative and quantitative methodologies, utilizing data from Shandong and Liaoning provinces. The findings underscore the significant role of growers' knowledge, technology compatibility, government support, and competitive pressure in driving the adoption of digital technology among growers, with male growers and those managing larger cultivation areas demonstrating higher adoption intensity. Digital technologies can enhance growers' economic benefits by reducing labor and input costs, increasing yields, and improving quality, with a 30.4% increase in economic benefits for each unit increase in adoption intensity of digital technologies. Technology promoters can use these findings to enhance growers' awareness, highlight the practical benefits, and offer agricultural socialized services to promote digital technology adoption.

Keywords: digital technology adoption; adoption intensity; growers; economic benefits; mixed methods

Citation: Geng, W.; Liu, L.; Zhao, J.; Kang, X.; Wang, W. Digital Technologies Adoption and Economic Benefits in Agriculture: A Mixed-Methods Approach. *Sustainability* **2024**, *16*, 4431. https://doi.org/10.3390/su16114431

Academic Editor: Thomas Bournaris

Received: 21 April 2024
Revised: 18 May 2024
Accepted: 21 May 2024
Published: 23 May 2024

1. Introduction

The integration of digital technologies (DTs), such as robotics, Internet of Things (IoT), and Artificial Intelligence (AI), represents the cornerstone of the fourth agricultural revolution (Agriculture 4.0), ushering in new opportunities for agriculture [1,2]. Governments worldwide are leveraging DTs to enhance productivity and improve farmers' livelihoods, aiming to address challenges related to climate change, food security, energy consumption, labor shortages, and environmental concerns, including fertilizer and pesticide inputs, as well as resource and energy efficiency [3–7]. Growers are also seeking ways to enhance profitability and production efficiency, with the aim of optimizing production decisions, mitigating costs, and elevating the value of agricultural products through the utilization of DTs [8]. The progress of digital agriculture varies among nations, yet the low adoption rate of DTs is a widespread issue, which is particularly pronounced in developing countries [9,10]. The United States Department of Agricultural Resource Management Survey (ARMS) indicated that in 2019, adoption rates of yield mapping, soil mapping, and Variable Rate Technology (VRT) for field crops such as corn, soybeans, and winter wheat ranged from approximately 5% to 25%, while the adoption rate of automatic steering and guidance systems exceeded 50% [11]. China exhibited a field planting informatization rate of 21.8% and a facility cultivation informatization rate of 25.3% in 2021. Africa has implemented several initiatives, yet farmers have limited access to DTs. So, what are the reasons behind the low adoption rate of DTs?

One major reason is the uncertainty often associated with the anticipated returns of new agricultural technologies [12,13]. The Internet of Food and Farm 2020 (IoF2020) trials in Europe showed IoT's positive contributions to yield, herbicide, and nitrogen fertilizer use in agriculture [14]. A decade-long Italian study on soil moisture sensors and Variable Rate Application (VRA) digital technologies recorded a 31% average increase in maize yield across 22 hectares, along with a 23% reduction in nitrogen fertilizer input [15]. A 2018 study involving 115 Iranian agricultural experts found that precision agriculture technologies can positively impact food quality, input costs, yield, income, and profitability [16]. Existing studies suggested that while DTs can significantly enhance economic benefits, the evidence is largely derived from relatively small-scale pilot projects and remains confined to certain countries and contexts. Evidence regarding widespread improvements in benefits from DTs is limited [17,18]. Some studies have also indicated inaccuracies and imprecisions in DTs in everyday agricultural operations, which may mislead farmers into making erroneous judgments and potentially lead to significant risks [19]. DTs widespread dissemination may be hindered by other factors such as small-scale farming [20–22], inadequate digital infrastructure, farmers' risk aversion, and low digital literacy among farmers [23].

Researchers have conducted studies on the influencing factors of DTs, focusing on crop types such as sugarcane [24], grapes [25], rice [26], corn, soybeans, and wheat [27], cotton [28] as well as mixed farms engaged in both cultivation and livestock [29,30]. Schnebelin (2022) focused specifically on the combined influence of farmers' socio-economic characteristics and cropping patterns on the adoption of DTs [31]. Ammann et al. (2022) [32] used Swiss outdoor vegetable as the research object and used the Delphi method to explore DTs adoption, highlighting the importance of financial support. Growers, acting as rational economic agents, engage in a deliberate process of adopting new technologies driven by benefit motives, while also being influenced by subjective perceptions and objective constraints [33,34]. However, only a limited number of studies thoroughly investigate the antecedents and consequences of growers' adoption of DTs.

Given the low adoption rate of DTs in agriculture, the ongoing debate regarding their economic benefits, and the presence of various barriers, this study examines the effectiveness of DT adoption and the influence of both internal and external factors among growers in Liaoning and Shandong provinces. It reflects the common issues in DTs adoption among growers, thereby providing valuable insights for the promotion of DTs in other countries and regions. Due to the diverse range of DTs adoption in agricultural production, we introduce the concept of "adoption intensity" to quantify the importance and degree of integration of DTs into growers' daily production or operational activities. This study addresses three pivotal research inquiries:

(1) What internal and external factors influence the intensity of DTs adoption among growers?
(2) How do these factors contribute to enhancing growers' adoption intensity of DTs?
(3) Has the heightened adoption intensity of DTs led to improved economic benefits for growers?

2. Research Design

This study employs a mixed-methods approach, integrating quantitative and qualitative research, to examine the factors that influence growers' adoption intensity of DTs and its impact on economic benefits. Quantitative research often tackles questions of "how much", whereas qualitative research explores "how". Employing a mixed-methods approach allows for the comparison of findings from both quantitative and qualitative methods, enriching the evidence base and yielding deeper insights [35,36]. The sequencing of qualitative and quantitative research hinges on the research topic. In exploratory designs, where qualitative research precedes quantitative research, initial insights and theoretical frameworks are established [37,38]. Conversely, in explanatory designs, qualitative research follows quantitative research to conduct detailed exploration and clarification of complex phenomena, as well as to identify unexpected variables [39]. Explanatory design is used in this study. Initially, hypotheses are formulated and tested with data from 435 growers in Shandong and Liaoning provinces. Subsequently, insights from semi-structured interviews with 15 growers are integrated to enrich the quantitative findings. The research design is summarized in Table 1.

Table 1. Mixed-methods research design.

Phase	Procedure	Outcome
	Literature study	Research hypothesis construction
Quantitative data collection	Structured questionnaire design	
	Pre-survey for 20 growers	
Quantitative data analysis	Formal survey of 435 growers in China	Sample size identify
	Software used: Stata 16	
	Confirmatory factors analysis	Reliability and validity
	Multicollinearity test	
	Negative binomial regression	Factors of DTs adoption
	Ordered Probit	
Qualitative data collection	Two-stage least squares (2SLS) and IV-Tobit	Economic benefits of DTs
	Semi-structured interview protocol design	
	Triangulation	
Qualitative data analysis	Formal interview of 15 growers	Sample size identify
	Qualitative data extraction	
	Inductive approach	Codes and themes
Interdata analysis	Compare, analyze, explain and discuss qualitative and quantitative results.	Confirmation of hypothesis Complementary findings

Source: Own elaboration based on Garrido-Moreno et al. (2024) [39].

3. Quantitative Study

This study conducts a quantitative analysis on 435 growers in China, employing a negative binomial regression model to investigate both the internal and external factors influencing growers' adoption intensity of DTs as well as 2SLS to explore the impacts of DTs adoption intensity on economic benefits.

3.1. Materials and Methods

3.1.1. Research Hypothesis

Drawing on the studies by Balogh et al. (2021) [40] and Wang et al. (2019) [41], factors influencing the intensity of DT adoption may be classified into internal and external realms. Internal factors relate to individuals' or organizations' traits when adopting innovation, while external factors involve market dynamics, competition, government support, access to credit, and external pressures. In this study, we examine grower's knowledge and technology compatibility as internal factors and consider government support and competitive pressure as external factors influencing DTs adoption intensity.

Grower's knowledge refers to the grower's degree of understanding, proficiency, and utilization of DTs. Lin and Lin (2008) [42] proposed that technological competence, which encompasses both tangible physical infrastructure and intangible knowledge, enables people to better integrate and leverage DTs effectively. Yadav et al. (2022) [43] emphasized that the application of DTs in agriculture yields abundant production data, and growers' understanding of these technologies is vital for optimizing production efficiency. A lack of essential knowledge is the primary barrier hindering decision-makers from adopting DTs [44]. Hence, the following Hypothesis 1 (H1) is proposed:

H1. *Grower's knowledge is positively correlated with their DTs adoption intensity.*

Technology compatibility refers to how seamlessly DTs integrate with established values, prior practices, and current necessities [45]. Wang et al. (2010) [46] argued that the successful adoption of DTs by farmers is influenced by the compatibility between new technology and existing technology, as well as the compatibility between the usage rules and management forms of new technology and the actual needs of farmers. Yoon et al. (2020) [47] found that farmers tend to adopt DTs that align with their existing resources or plans, while they may reject technologies perceived as incompatible, fearing negative consequences. The greater the compatibility between DTs and the current work of farmers, the higher the intensity of its adoption. Hence, the following Hypothesis 2 (H2) is proposed:

H2. *Technology compatibility is positively correlated with the DTs adoption intensity of growers.*

Government support refers to the degree of policy and financial support required to process DTs. Past studies have demonstrated the significant role of government support in encouraging farmers to adopt information technologies [48]. Farmers across various geographic regions have experienced both economic and non-economic benefits through government agencies' support in smart farming adoption, aiding in administrative assistance and financial sustainability [49]. Wang et al. (2019) [41] noted the complexity and high cost of investment associated with DTs, highlighting the need for government support in providing funding, skills, resources, and other support to farmers for the introduction and utilization of technologies.. Hence, the following Hypothesis 3 (H3) is proposed:

H3. *Government support is positively correlated with the DTs adoption intensity of growers.*

Competitive pressure refers to the level of perceived pressure experienced by growers from competitors within the industry. This pressure compels farmers to adopt new technologies in order to maintain a competitive advantage [50]. Wei et al. (2015) [51] posited that the competitive pressure positively influences the adoption of new technological innovations. Early adopters of these technologies can showcase their benefits, raising awareness among decision-makers and encouraging adoption. De Prieelle et al. (2022) [52] highlighted the introduction of new management techniques and technologies by agricultural organizations to address competitive pressures. Farms currently utilizing smart agricultural technologies demonstrate improved production efficiency. Hence, the following Hypothesis 4 (H4) is proposed:

H4. *Competitive pressure is positively correlated with the DTs adoption intensity of growers.*

Direct economic benefits and enhanced productivity or profitability serve as pivotal objectives and driving forces behind farmers' adoption of technology [53,54]. Researchers have analyzed the role of DTs in enhancing growers' economic benefits based on two dimensions: cost reduction and efficiency improvement. Bahn et al. (2021) [55] found that DTs can reduce production costs by controlling agricultural inputs and labor. The studies of Schimmelpfennig et al. (2016) [56] and Erdem and Ağır (2024) [57] have shown that DTs can enhance agricultural productivity and yields for farmers, leading to increased economic benefits. Hence, the following Hypothesis 5 (H5) is proposed:

H5. *DTs adoption intensity of growers is positively correlated with its economic benefits.*

3.1.2. Data Collection

This study was conducted in Shandong and Liaoning provinces, both of which are major agricultural regions in northern China (see Figure 1). Shandong ranks second nationwide in agricultural output value and consistently ranks in the top 10 for grain, vegetable, and fruit production. Liaoning contributes 3.0% of the national sowing area but produces 3.6% of the country's grain. In 2022, Liaoning produced 8.797 million tons of fruit and 20.554 million tons of vegetables. The formal survey, conducted from April to August 2023, utilized a stratified random sampling method and convenience sampling method through the utilization of structured questionnaires. In Liaoning and Shandong provinces, 2–4 prefecture-level cities were randomly selected in each province, with five sample towns randomly chosen from each prefecture-level city. Then, 10–15 growers were randomly surveyed in each town through face-to-face household surveys. The convenience sampling method involved collaborating with agricultural industry associations to identify sample growers, wherein the research team directly assisted growers in completing questionnaires to ensure data reliability. A total of 435 valid samples were collected through the random sample and convenience sample method.

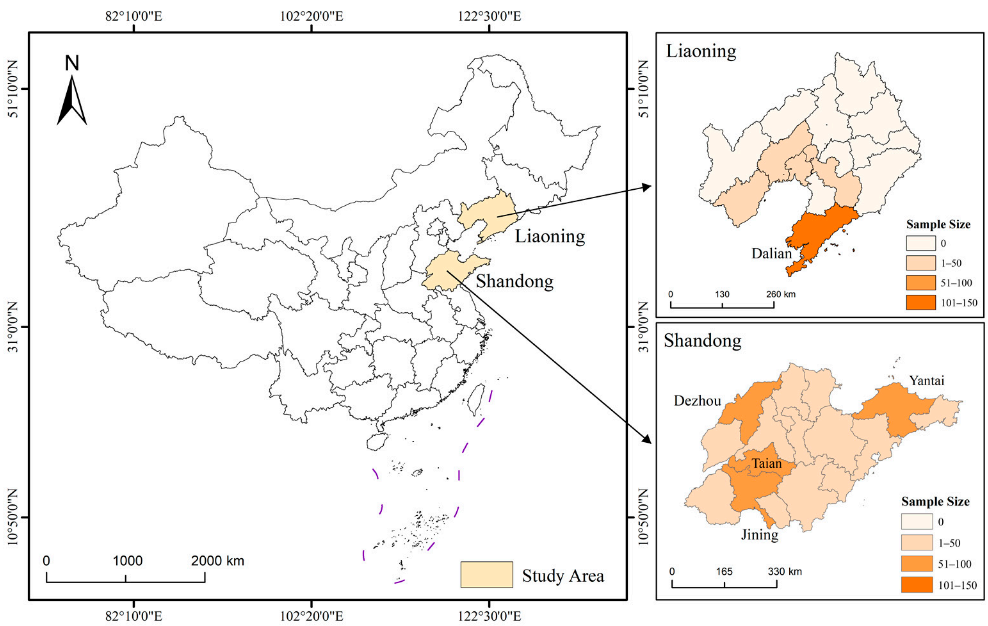

Figure 1. Research region in Liaoning and Shandong province.

Before the main survey, we conducted a preliminary survey involving 20 growers to refine the questionnaire. Based on the respondents' feedback, we rephrased the Likert-scale questions into more accessible language to minimize inaccuracies arising from misunderstandings. Before growers filled out the questionnaire, we introduced the purpose and content of the survey. The questionnaire could only be completed after obtaining the respondent's consent, ensuring that personal privacy was not compromised. The growers were adults proficient in smartphone usage, belonging to the categories of grain, vegetable, and fruit growers.

The structured questionnaire was divided into three parts: individual and agricultural production characteristics of growers; adoption status of DTs; as well as factors influencing growers' adoption of DTs. At the farm level, DTs encompass precision agricultural equipment, robotics, agronomic advice and information, and farm management platforms [58]. In selecting the DTs for this study, we comprehensively considered the current state of DTs in Chinese agriculture and incorporated findings from preliminary research. We focused on technologies that are widely promoted and already in use in practical agricultural production. Four DTs were analyzed in this study: digital sensors, precision irrigation systems, precision fertilization systems, and unmanned aerial vehicles (UAVs). The descriptions of each DT can be found in Table 2. Internal and external factors were adapted from mature scales in previous studies, with each factor comprising three measurement items on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Detailed information regarding the questionnaire can be referenced in Appendix A.

Table 2. Description of the digital technologies included in this study.

Digital Technologies	Descriptions
Digital sensors	Real-time monitoring, collecting, transmitting, and storing data on temperature, humidity, soil moisture, nutrient levels, and carbon dioxide concentration in designated areas, while also automatically controlling and providing feedback based on preset conditions [59].
Precision irrigation systems	Based on crop water requirements and soil moisture conditions, irrigation schedules, timing, and water flow rates should be systematically devised to achieve precise control and management of irrigation [60].
Precision fertilization systems	By monitoring factors such as soil nutrient levels, crop growth status, and meteorological conditions, rational adjustments to fertilizer formulations and application rates have been made, resulting in increased fertilizer efficiency and nutrient utilization by crops [61].
Unmanned aerial vehicles	UAVs are utilized in agricultural production to facilitate tasks such as field monitoring, crop growth analysis, and precision spraying [62].

3.1.3. Variable Measure

Explained variables: When examining the factors influencing the adoption intensity of DTs, the explained variable is the DTs adoption intensity. Drawing on the study by Isgin et al. (2008) [63], "DTs adoption intensity" is quantified by the number of DTs growers have actually adopted, with values ranging sequentially from 1 to 4 in this study. When studying the influence of growers' DTs adoption intensity on economic benefits, economic benefits are the explained variable, which is measured by the average net profit from crop cultivation over the past three years.

Explanatory variables: When examining the factors influencing the adoption intensity of DTs, grower's knowledge, technology compatibility, government support and competitive pressure are explanatory variables. All items listed among these variables were derived from previous studies. Grower's knowledge and government support were adapted from the work of Yoon et al. (2020) [47], which measured grower's knowledge in terms of understanding, proficiency, and utilization, while government support was assessed through policies and funding, projects, and technical support. Technology compatibility was adapted from Tiago (2014) [64], and was evaluated based on the compatibility of digital technologies with growers' current needs, previous practices, and cultural values. Competitive pressure was derived from Junior et al. (2019) [65], measured by the competitive environment, competitive advantage, and peer effects. When studying the influence of growers' DTs adoption intensity on economic benefits, DTs adoption intensity is an explanatory variable.

Control variables: This study considers four individual characteristics as well as four agricultural production characteristics of growers as control variables: age, sex, education years, cultivation experience, training participation, cultivation area, labor size, and crop type [66–70]. This study also controlled for the impact of the COVID-19 pandemic on agricultural production [71].

Instrumental variables (IV): To mitigate potential endogeneity concerns within the model, this study draws upon the studies of Li et al. (2023) [72] and An (2015) [73], utilizing "DTs adoption rate of local peers" as an IV to investigate the impacts of growers' DTs adoption intensity on economic benefits. IVs should exhibit a high correlation with potentially endogenous explanatory variables while maintaining independence from the model's error term [74]. Peer effects shape growers' expectations regarding the benefits of information channels, thereby driving the intensity of DTs adoption. And there is no direct link between peer DTs adoption and growers' economic benefits. The "DTs adoption rate of local peers" fulfills the criteria for instrumental variables in this study [75].

3.1.4. Regression Analysis

Poisson regression and negative binomial regression (NBREG) are widely used count regression models in various research domains [76]. In this study, the variance of DTs adoption intensity was found to be 1.108 (SD = 1.053), exceeding the mean value of 1.016. Given the dispersion, a negative binomial regression model was employed instead of a Poisson regression model [77,78]. The equation of NBREG is as follows:

$$\mu_{ik} = \beta_{0ik} + \beta_1 x_{1ik} + \cdots + \beta_4 x_{4ik} + \beta_n x_{nik} + \theta \quad (1)$$

where i refers to the grower i.

k refers to the city where the grower i is located.

β_0 is the intercept term.

β_1 *to* β_n refers to the coefficient of variables.

x_{1ik} *to* x_{4ik} refers to the grower's knowledge, technology compatibility, government support, and competitive pressure.

x_{nik} refers to the control variables.

μ_{ik} indicates the expected count for the grower i.

θ is the scale parameter of the negative binomial distribution.

We employed a two-stage least squares model (2SLS) to analyze the impact of grower' DT adoption intensity on their economic benefits. This approach assists in mitigating potential endogeneity issues and estimation biases related to the limited explanatory variables. The procedure involves two sequential steps, effectively isolating the influence of endogenous variables on the dependent variable while considering the potential effects of IV and control variables [79]. The first- and second-stage regressions of 2SLS are illustrated by the equations below:

First stage:

$$IV_{ik} = \beta_{0ik} + \beta_1 x_{1ik} + \beta_2 x_{2ik} + \epsilon_{ik} \quad (2)$$

Seond stage:

$$\mu_{ik} = \beta_{0ik} + \beta_1 IV_{ik} + \beta_2 x_{2ik} + \epsilon_{ik} \quad (3)$$

IV_{ik} refers to the DTs adoption rate of local peers.

μ_{ik} refers to economic benefits.

x_{1ik} refers to the DTs adoption intensity.

x_{2ik} refers to the referenced control variables.

ϵ_{ik} refers to the random perturbation term.

3.2. Results of Quantitative Study

3.2.1. Descriptive Statistics

The individual characteristics and agricultural production traits of the 435 growers are detailed in Table 3. To improve the interpretability and numerical stability of the regression coefficients, the variables were scaled as follows: cultivation experience was multiplied by 10, cultivation area by 1000, labor size by 100, and economic benefits by 10,000. On average, the growers who responded to the survey were approximately 49.230 years old, with a predominance of male growers. Most growers have attained an education up to middle or high school level, with an average education duration of 10.897 years. They boast an average cultivation experience of more than 28 years. Over the past three years, growers have engaged in an average of 3.051 training sessions. The average cultivation area is relatively substantial, measuring 206 mu. Among the 435 growers, 210 are dedicated to grain cultivation, 142 to fruit cultivation, and 83 to vegetable cultivation. Each grower employs an average of about 10 fixed laborers, yielding an average net profit of CNY 6830 per mu per year. The average intensity of DTs adoption among adopters is 1.016, with a minimum of 1 and a maximum of 4. Additionally, the average peer adoption rate of DTs stands at 0.324. The average impact of COVID-19 on growers is 2.131, falling between low and moderate impacts.

Table 3. Individual and agricultural production characteristics of surveyed growers (n = 435).

Variables	Descriptions	Mean	Standard Deviation
Age	Age of the growers in years.	49.230	9.021
Sex	Sex of the growers (1 = male, 0 = female).	0.726	0.446
Education years	Years of formal education of growers.	10.897	2.580
Cultivation experience (10 years)	Years of experience in cultivation for growers.	2.835	1.054
Training participation	The number of times growers have participated in digital technology training organized by government and agricultural industry associations over the past three years.	3.051	3.587
Cultivation area (1000 mu)	Cultivation area of growers.	0.206	0.331
Labor size (×100)	Fixed number of labor force.	0.099	0.243
Crop type	Primary type of cultivated crop (Grains = 1, Fruits = 2, Vegetables = 3).	1.708	1.292
Economic benefits (10,000 yuan/mu)	Average net profit from cultivation over the past three years.	0.683	0.768
DTs adoption intensity	Number of digital technologies (DTs) adopted by growers.	1.016	1.053
DTs adoption rate of local peers (0~1)	Proportion of growers engaged in digitalized cultivation within the same county.	0.324	0.299
Impacts of COVID-19	Impact of COVID-19 on agricultural production and operations over the past three years (No impacts = 1, Low impacts = 2, Moderate impacts = 3, High impacts = 4).	2.131	0.822
Grower's knowledge	The grower's degree of understanding, proficiency, and utilization of a DT.	11.531	2.268
Technology compatibility	The degree to which a DT fits with the existing values, previous practices, and current needs.	10.189	1.922
Government support	The degree of policy, finance, and technical support from government to process DTs.	11.340	2.259
Competitive pressure	The degree of perceived pressure experienced by growers from competitors within the industry.	11.407	1.979

Figure 2 illustrates the adoption status of 435 growers regarding four DTs. In total, 264 growers have adopted at least one DT, accounting for 60.7% of the respondents, while 39.3% have not adopted DTs. Among the adopters, 33.1% of growers have adopted one DT, and 16.1% of growers have adopted two DTs. There are relatively fewer growers who have adopted three or more DTs.

From Figure 3, it is evident that the technology with the highest adoption rate is UAVs, with 149 growers adopting these, accounting for a 34.3% adoption rate. The second-highest adoption rate is observed for precision irrigation systems, which were adopted by 120 growers, with an adoption rate of 27.6%. Precision fertilization systems rank third, with 105 growers adopting these systems, representing an adoption rate of 24.1%. The adoption rate of sensors is relatively low, reaching 15.6%.

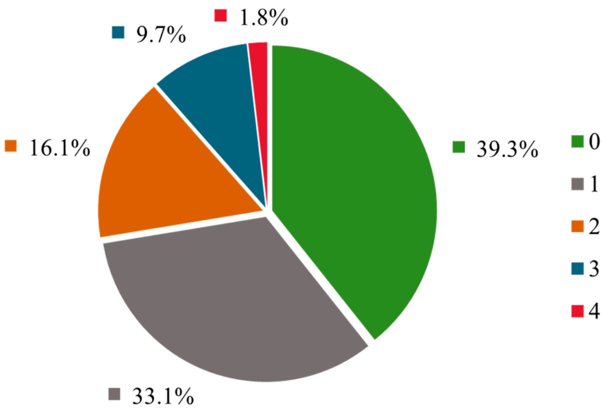

Figure 2. Digital technologies adoption intensity of growers (n = 435).

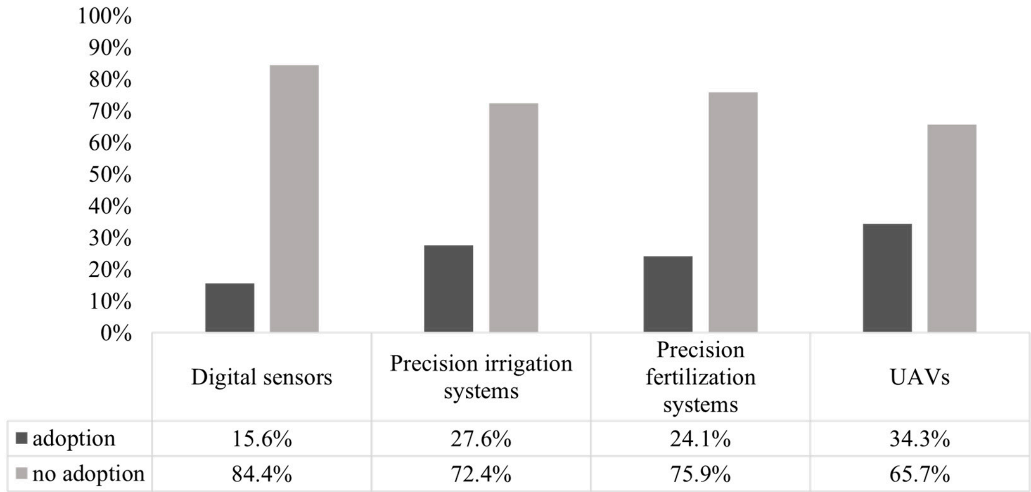

Figure 3. The adoption proportion of each digital technology (n = 435).

3.2.2. Test of Reliability and Validity

Before proceeding with the regression analysis, we assessed the reliability and validity of the sample data. Validity testing gauges how well measurement indicators represent intended meanings, while reliability testing assesses questionnaire measurement consistency. Using Cronbach's α coefficient, we evaluated the reliability of the questionnaire data (see Table 4). All factors exhibited α values between 0.828 and 0.944, surpassing the 0.70 threshold, indicating robust reliability and internal consistency [80]. The standardized factor loadings of the measurement items in this study range from 0.761 to 0.956, all factors with KMO > 0.600 and Bartlett (p) < 0.001, suggesting that the indicators in the measurement tool or questionnaire adequately represent the constructed concepts, thereby enhancing the construct validity of the tool [81,82]. The average variance extracted (AVE) values and composite reliability (CR) values exceeded thresholds of 0.5 and 0.7, indicating the convergent validity of the measurement model [83]. Overall, our measurement model exhibits strong reliability and validity.

Table 4. Testing the reliability and validity of measurement items.

Variables	Standardized Factor Loadings	KMO	Bartlett (p)	α	AVE	CR
Grower's knowledge						
Grower's knowledge 1	0.915	0.680	0.000	0.830	0.753	0.901
Grower's knowledge 2	0.850					
Grower's knowledge 3	0.836					
Technology compatibility						
Technology compatibility 1	0.912	0.657	0.000	0.828	0.746	0.898
Technology compatibility 2	0.910					
Technology compatibility 3	0.761					
Government support						
Government support 1	0.943	0.769	0.000	0.944	0.899	0.964
Government support 2	0.956					
Government support 3	0.946					
Competitive pressure						
Competitive pressure 1	0.867	0.703	0.000	0.886	0.817	0.930
Competitive pressure 2	0.940					
Competitive pressure 3	0.903					

Notes: α = Cronbach's alpha; KMO = Kaiser–Meyer–Olkin value; AVE = average variance extracted; CR = composite reliability.

Before conducting NBREG and 2SLS regression, we performed multicollinearity tests. The results indicated no significant multicollinearity (see Table 5), as there were no tolerance values below 0.1 or Variance Inflation Factor (VIF) values exceeding 5 [84,85].

Table 5. Multiple collinearities of the diagnosis.

Factors Influence on DTs Adoption Intensity			DTs Adoption Intensity on Economic Benefits		
Variable	**VIF**	**1/VIF**	**Variable**	**VIF**	**1/VIF**
Technology compatibility	2.170	0.460	Age	1.260	0.795
Competitive pressure	2.160	0.463	Education years	1.240	0.809
Government support	1.590	0.629	Crop type	1.230	0.814
Grower's knowledge	1.420	0.704	Labor size	1.210	0.827
Age	1.270	0.786	Cultivation area	1.190	0.842
Education years	1.240	0.803	DTs adoption intensity	1.190	0.843
Labor size	1.230	0.811	Cultivation experience	1.150	0.872
Cultivation area	1.200	0.835	Training participation	1.050	0.954
Crop type	1.190	0.842	Impacts of COVID-19	1.030	0.972
Cultivation experience	1.160	0.861	Sex	1.020	0.978
Training participation	1.060	0.946			
Impacts of COVID-19	1.030	0.967			
Sex	1.030	0.974			
Mean VIF	1.370		Mean VIF	1.160	

3.2.3. Factors Influencing DTs Adoption Intensity

We employ the NBREG model to reveal the factors influencing DT adoption intensity (see Table 6). Model 1 depicted the regression analysis with a subset of control variables, whereas Model 2 accounted for all the individual characteristics and agricultural production characteristics of growers, alongside the influence of the COVID-19 pandemic. The results showed that the grower's knowledge, technology compatibility, government support and competitive pressure had significant positive correlations with the adoption intensity of DTs, regardless of whether the variables were being controlled. H1, H2, H3 and H4 were verified.

Table 6. Impact of internal and external factors on DTs adoption intensity: negative binomial regression and ordered probit.

Variables	Negative Binomial Regression Model		Ordered Probit
	Model 1	Model 2	Model 3
Grower's knowledge	0.177 ** (0.081)	0.160 ** (0.063)	0.185 *** (0.056)
Technology compatibility	0.135 *** (0.035)	0.118 *** (0.039)	0.111 ** (0.056)
Government support	0.138 *** (0.052)	0.102 ** (0.046)	0.115 ** (0.048)
Competitive pressure	0.122 *** (0.047)	0.100 *** (0.039)	0.104 ** (0.043)
Age	−0.009 (0.006)	−0.007 (0.007)	−0.006 (0.008)
Sex	0.198 ** (0.080)	0.187 ** (0.090)	0.238 ** (0.099)
Education years	0.066 ** (0.026)	0.039 (0.027)	0.043 (0.051)
Cultivation experience	−0.017 (0.035)	−0.006 (0.038)	0.004 (0.052)
Training participation		0.017 (0.018)	0.019 (0.024)
Cultivation areas		0.251 * (0.153)	0.289 (0.213)
Labor size		0.184 (0.118)	0.398 ** (0.194)
Fruits		−0.233 *** (0.070)	−0.378 *** (0.084)
Vegetables		−0.842 * (0.453)	−0.931 *** (0.339)
Impacts of COVID-19	Controlled	Controlled	Controlled
_cons	−0.435 (0.643)	−0.242 (0.514)	
Pseudo R2	0.047	0.081	0.094
Wald chi2	323.480	18,324.830	10,861.520
Prob > chi2	0.000	0.000	0.000
N	435	435	435

Notes: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are presented in parentheses.

Regrading internal factors, grower's knowledge significantly enhances DTs adoption intensity at the 5% significance level. Specifically, for each unit increase in grower's knowledge, there is a corresponding 16% rise in adoption intensity. Growers who possess a deep understanding of DTs functionalities and agricultural prospects exhibit heightened adoption intensity. Similarly, technology compatibility significantly enhances DTs adoption intensity at the 1% significance level. For each unit increase in compatibility, there is a 11.8% increase in DTs adoption intensity. This suggests that growers with higher compatibility between DTs and landowner values, agricultural needs, local farm conditions, and management practices tend to adopt DTs more intensively.

Regarding external factors, government support significantly enhances the intensity of DTs adoption at a 5% significance level. For each unit increase in government support, growers' adoption intensity of DTs rises by 10.2%. This underscores the crucial role of government policies and incentives in driving technology adoption. Competitive pressure significantly enhances the intensity of DTs adoption at a 1% significance level. For each unit increase in competitive pressure, growers' adoption intensity of DTs rises by 10%.

Besides, sex and cultivation area show significance at the 5% and 1% levels, respectively, indicating higher DTs adoption intensity among male growers and those with a larger cultivation area. Fruit and vegetable growers exhibit lower DTs adoption intensity compared to grain growers.

To ensure robustness, NBREG was replaced with ordered probit regression to analyze determinants of DTs adoption intensity (see Model 3). The result show that growers' intensity to adopt DTs was affected by the growers' knowledge, technology compatibility, government support and competitive pressure significantly. These findings affirm the robustness of regression results in Model 2.

3.2.4. Impact of DTs Adoption Intensity on Economic Benefits

Table 7 presents the regression outcomes detailing the influence of growers' DTs adoption intensity on their economic benefits, while controlling for individual and agricultural production characteristics of growers, along with the impacts of the COVID-19. In the first stage (Model 4) of the 2SLS regression, economic benefits exhibited a positive correlation with DTs adoption intensity ($\beta = 1.140$, $p < 0.01$). The p-value of the Kleibergen–Paap rk LM statistic was less than 0.01, indicating the model under identification. Conversely, the Cragg–Donald Wald F statistic stood at 45.576, surpassing the 10% critical value of 16.38, suggesting no issues with weak instruments. Subsequently, in the second stage of 2SLS (Model 5), a significant association between DTs adoption intensity and economic benefits was observed, revealing a 30.4% rise in economic benefits for each unit increase in DTs adoption intensity. For robustness, Model 6 substituted 2SLS with IV-Tobit. The regression coefficients and significance of DTs adoption intensity displayed no substantial deviation between 2SLS and IV-Tobit. This implies that both Model 5 and Model 6 affirm H5, ensuring the robustness of the regression outcomes.

Table 7. The impacts of DTs adoption intensity on economic benefits.

Variables	IV	Economic Benefits	
	Model 4 (2SLS)	Model 5 (2SLS)	Model 6 (IV-Tobit)
DTs adoption intensity	1.140 ***	0.304 **	0.304 **
	(0.422)	(0.150)	(0.154)
Control variables	Controlled	Controlled	Controlled
_cons	0.268	−0.558	−0.527
	(0.472)	(0.371)	(0.421)
Centered R2		0.241	
Wald chi2			4761.65
Prob > F		0.000	
Prob > chi2			0.000
N	435	435	435

Notes: *** and ** indicate significance at 1% and 5% levels, respectively. Robust standard errors are presented in parentheses.

3.2.5. Sensitivity Analysis

To examine potential omitted variables and their impact on the regression, this study employs a sensitivity analysis based on Oster (2019) [86] approach, focusing on the impact of growers' digital technology adoption intensity on their economic benefits. The true coefficient estimation is performed using $\beta^* = \beta^*(Rmax, \delta)$, where $Rmax$ represents the maximum goodness-of-fit of the regression equation when all unobservable variables are accounted for, and δ is the selection proportion indicating the relationship strength between the core explanatory variables and both observable and unobservable variables. A δ value of one indicates equal importance between observable and unobservable variables.

Following the method described by Oster (2019) [86], we set $Rmax$ = 1.3R, where R is the current regression equation's goodness of fit, allowing for a 1.3-fold increase in the goodness of fit. If δ exceeds the critical value of 1, the test is passed. The results of the sensitivity test are presented in Table 8. When $Rmax$ = 1.3R and β^* = 0, $\delta > 1$, indicating a passing result. This suggests that omitted variables have a negligible effect on the estimated outcomes, as they did not lead to substantial bias in the estimation results. Therefore, the estimates from the baseline regression are robust.

Table 8. Sensitivity analysis of DTs adoption on economic benefits.

Dependent Variables Standards	Check	Estimation Results	Test Results
Economic benefits	$\delta > 1$	$\delta = 8.165$	Yes

4. Qualitative Study

This section employs semi-structured interviews with 15 growers, utilizing a triangulation and inductive approach to bolster and enrich the findings derived from quantitative research. Subsequent sections outline the qualitative research methodology and highlight key findings.

4.1. Method and Material

4.1.1. Data Collection

Growers were required to complete the questionnaire prior to the interviews, during which their contact details were recorded for those expressing interest in further in-depth discussions. Growers were selected based on specific criteria, including their adoption or inclination towards adopting DTs, or having a minimum three-year history of DTs application. Twenty-five growers agreed to participate in the interviews, from whom we ultimately selected 15 growers (see Table 9). The interview guidelines were tailored to align with the research objectives, and each interviewee was interviewed sequentially by a team consisting of 2–3 interviewers. Following an initial discussion on the cultivation status of growers and their adoption of DTs, we posed open-ended questions such as "What factors drive or hinder your adoption of DTs?" and "How do you perceive the effectiveness of adopting DTs?" As the interviews progressed, we delved deeper into key concepts such as grower's knowledge, technology compatibility, government support, and competitive pressure. The interviews concluded within a one-hour timeframe.

Table 9. Individual and agricultural production characteristics of interviewed growers (n = 15).

Grower ID	Cultivation Area (mu)	Cultivation Experience	Digital Technology Adoption	Crop Type
HG 01	5	40	Digital sensors	Vegetable
HG 02	11	10	Digital sensors	Fruit
HG 03	18	21	Digital sensor, precision irrigation system, precision fertilization system	Fruit
HG04	30	24	Digital sensor, precision irrigation system, precision fertilization system	Fruit
HG 05	40	35	Digital sensor, precision irrigation system, precision fertilization system	Fruit
HG 06	100	38	Precision irrigation system; precision fertilization systems	Vegetable
HG 07	100	25	UAVs	Vegetable
HG 08	106	29	Precision irrigation systems, precision fertilization systems	Fruit

Table 9. *Cont.*

Grower ID	Cultivation Area (mu)	Cultivation Experience	Digital Technology Adoption	Crop Type
HG 09	200	31	Digital sensor, precision irrigation system, precision fertilization system	Fruit
HG 10	1000	10	Precision irrigation systems; precision fertilization systems	Fruit
HG 11	3	36	Non-adopter	Vegetable
HG 12	7	37	Non-adopter	Vegetable
HG 13	8	18	Non-adopter	Vegetable
HG 14	16	31	Non-adopter	Fruit
HG 15	24.5	29	Non-adopter	Vegetable

4.1.2. Data Analysis

We utilized an inductive approach to analyze the qualitative data, distilling said data into concise statements or insights [87]. Before commencing qualitative data analysis, we consolidated the interview transcript into a single document, marking the formal initiation of the six-step data analysis process [88]. Firstly, the authors familiarized themselves with the data by repeatedly reviewing the interview transcripts. Secondly, they generated codes for segments of information relevant to the core research questions. Thirdly, they reviewed and analyzed the coded data to identify themes or subthemes. Fourthly, they scrutinized the themes or subthemes, adding or removing those that did not align with the research objectives. Fifthly, they conducted detailed analysis, defining and naming the themes. Lastly, the authors reached a consensus on the research findings and drafted the results of data analysis.

4.2. Results of Qualitative Study

4.2.1. Factors Influencing DTs Adoption Intensity

Based on sample analysis, it became apparent that a deficiency in DTs knowledge may impede growers' adoption of such DTs. This is particularly evident among smallholder farmers such as HG11 and HG13 (see Table 10). Some smallholders perceive traditional farming methods reliant on experiential knowledge as adequate for meeting production needs, indicating that embracing new technologies necessitates both time and a cultural shift. Other smallholders possess an understanding of DTs but lack clarity regarding their specific benefits, resulting in a reserved stance toward their adoption. Another group of growers, exemplified by HG05, consists of large-scale growers who are pioneers in adopting DTs. They typically possess extensive industry connections and social networks, along with more experience and financial resources. Consequently, they can leverage various channels to access the latest cultivation knowledge and technology, and they have a deeper understanding of the capabilities and functionalities of DTs.

Table 10. Growers' statements regarding knowledge.

Grower's Knowledge	
HG05	[...] I'm an early adopter of DTs. I'm always willing to learn and try new technologies, and I plan to use some more precise and intelligent devices in the next 5 years. [...]
HG11	[...] I've heard about and have some understanding of DTs, but I'm not clear on the specific benefits it can bring to me. [...]
HG13	[...] I don't understand the intricacies of DTs, I can determine when to ventilate and when to irrigate based on my experience. [...]

Technology compatibility emerges as a pivotal factor driving growers' adoption of DTs. Growers highlight the current deficiency in DTs' compatibility across different crop types, cultivation areas, and crop growth cycles (see Table 11). Digital equipment predominantly caters to a select few high-value vegetable crops, rendering them unsuitable for relatively low-tech crops like onions and spinach, where traditional cultivation and management methods are deemed more suitable (HG12). Given the efficiency and cost considerations associated with DTs, larger-scale growers are better positioned to adopt these technologies to manage the operational challenges of large-scale farming (HG07). However, even among large-scale growers, instances of incompatibility with DTs may arise. Limitations inherent in DTs may hinder their ability to adjust pesticide dosage and irrigation timing according to crop growth status, making it challenging to achieve results comparable to manual methods. Therefore, further development and improvement of DTs may be necessary (HG09).

Table 11. Growers' statements regarding technology compatibility.

Technology Compatibility	
HG07	[...] UAVs spraying is only suitable for large-scale farmland. With 100 mu of land on my farm, we meet the scale requirements for drone spraying. [...]
HG09	[...] The growth of trees varies, so precise irrigation can only result in uniform spraying, while manual application allows for dosage adjustment based on different trees. [...]
HG12	[...] I believe technology compatibility is very important. For example, manual labor is the only option for cultivating onions, while DTs are more suitable for cucumbers and tomatoes. [...]

The analysis of the sample indicates a strong correlation between growers' adoption of DTs and comprehensive government support. Growers who have embraced DTs have cited a range of supportive policies, notably those promoting precision irrigation systems and precision fertilization systems (see Table 12). Initiatives such as infrastructure provision, advanced equipment, training sessions, and financial support are aimed at mitigating financial and technological risks, thereby fostering DT adoption among growers. These efforts have yielded positive outcomes, underscoring the pivotal role of government support in driving agricultural digitization, as reinforced by the interview findings.

Table 12. Growers' statements regarding government support.

Government Support	
HG04	[...] Nine years ago, I installed precision irrigation devices during greenhouse construction, subsidized by the government at ten thousand yuan per mu for circuitry and equipment. [...]
HG06	[...] The government supports through the provision of network infrastructure and DTs equipment to demonstration households. [...]
HG08	[...] The government facilitates exchanges on technologies among local producers, offering brief on-site training sessions to encourage technology adoption. [...]

The interview findings emphasize the constructive influence of peer effects on growers' adoption of DTs. Growers who have effectively integrated DTs may motivate their peers to adopt similar approaches (see Table 13). For example, HG01 was inspired by the favorable results observed in their peers' utilization of DTs, and therefore chose to implement technologies like digital sensors and precision irrigation systems. Although some of the growers have yet to adopt DTs, they also acknowledged being influenced by their peers (HG14 and HG15).

Table 13. Growers' statements regarding competitive pressure.

Competitive Pressure	
HG01	[...] I observed the effects on my peers in the same village who implemented precision irrigation. They were able to save 10–20% on water and fertilizer costs, which prompted me to follow suit. [...]
HG14	[...] Once demonstration households demonstrate positive economic benefits, everyone will be motivated to learn from and emulate their adoption. [...]
HG15	[...] China is currently vigorously promoting digital agriculture, and competitors and partners in the vicinity did have impacts on me. [...]

4.2.2. Impact of DTs Adoption Intensity on Economic Benefits

Most growers highlighted the efficacy of DTs across five dimensions: yield, quality, labor cost, irrigation water usage, and pesticide usage (see Table 14). The primary benefits included a notably higher crop yield and quality, along with reduced labor cost, leading to increased profitability. Specific economic gains included a 20% boost in yield and quality (HG05), labor cost reductions of 20–30% (HG02), and a 30% decrease in water and pesticide usage (HG04) (see Table 15). Only one grower (HG03) reported suboptimal performance of digital sensors due to equipment quality issues, widespread temperature measurement errors, and equipment damage. He believed that achieving the desired outcome without manual intervention was difficult with this DT. He indicated that the decision to adopt would depend on the advancement level of DTs in the future.

Table 14. Economic benefits.

Economic Benefits	Grower
Increase yield	HG01, HG05, HG06, HG07
Improve quality	HG01, HG05, HG06, HG07, HG10
Reduce labor costs	HG02, HG04, HG05, HG07, HG08
Decrease irrigation water usage	HG04, HG05
Decrease pesticide usage	HG04
No effects	HG03

Table 15. Growers' statements regarding economic benefits.

Economic Benefits	
HG02	[...] I am relatively satisfied with the use of UAVs for spraying pesticides on vegetables. Labor costs can be reduced by 20% to 30%, yield and quality were improved. [...]
HG04	[...] The benefits of using DTs are evident in water and pesticide savings, with a reduction of 30% in both. [...]
HG05	[...] After applied precision irrigation systems, labor costs for three greenhouses can be reduced by over 10,000 yuan, and yield and quality can increase by 20%. [...]

5. Discussion

In this study, employing a mixed-method approach, we quantitatively analyze data from 435 growers to investigate the influence of managerial knowledge, technology compatibility, government support, and competitive pressure on DT adoption intensity. Additionally, we delve into the correlation between adoption intensity and economic benefits. Our qualitative analysis, based on interviews with 15 growers, further strengthens and elaborates on our findings. These findings hold substantial significance for promoting DT adoption among growers in the North China region and beyond.

5.1. Discussion of Factors Influencing DTs Adoption Intensity

We discovered that grower's knowledge is a significant factor in facilitating adoption intensity of DTs. These findings were aligned with the results of prior studies [89,90]. Technology adoption typically begins with acquiring and understanding knowledge about technology usage in production, which varies based on individual and contextual factors, depending on available information [91]. Qualitative findings revealed that non-adopters of DTs lack an initial understanding of the functionalities and advantages of DTs. Limited access to information channels and weaker receptivity to DTs among some growers, especially small-scale growers, often hinder their adoption capacity. As a result, many DTs tend to cater to the high-tech and capital-intensive growers, inadvertently excluding or marginalizing certain grower demographics [92]. Growers can obtain more knowledge through diverse sources such as technology provider training, informal networks, peer observation, and social media [93].

In line with prior research, technology compatibility is crucial for growers who are adopting and diffusing DTs [94,95]. The adoption of DTs may be constrained if there is a lack of compatibility between the technologies and users' existing values, needs, and experiences [96]. Growers are faced with a range of available DTs, not all of which are compatible with their plots, nor do all DTs necessarily provide benefits to them. Due to the insufficient maturity of DTs themselves, there is a lack of compatibility with various cultivation areas, cultivation modes, and crop types, thereby impeding the current capability to meet the production demands of all crops [97]. Therefore, growers need to fully understand the characteristics and functionalities of DTs and assess their own capabilities before making adoption decisions [18]. Pre-emptive agricultural advisory services are crucial.

Quantitative and qualitative analysis further reveals that government support significantly promotes growers' adoption intensity of DTs. Government support measures encompass infrastructure development, investment in advanced technological equipment, establishment of demonstration sites, and dissemination of successful cases. These research findings align with the findings of Rose et al. (2016) [98] and Sun et al. (2016) [99]. The supportive role of government is evident not only among Chinese growers but also in Iran. A study revealed that farms with access to government funding, technology, and management resources demonstrate a greater propensity to adopt new technologies. This is attributed to the assurance provided by robust system software and hardware design, as well as effective daily equipment maintenance [100].

Competitive pressure significantly correlates with DTs adoption intensity, aligning with prior studies [101,102]. DTs are regarded as essential for growers aiming to sustain competitiveness [103,104]. A notable phenomenon of competitive pressure manifests in the form of peer effects. Peer effects are frequently observed in growers' adoption intensity of DTs, wherein individuals are more inclined to adopt DTs if their peers or competitors do so. Krishnan et al. (2014) [105] and Ferrali et al. (2019) [106] identified similar trends in their studies on agricultural technology adoption in Ethiopia and Uganda, respectively.

Moreover, the individual characteristics of growers play a crucial role in determining DTs adoption. Males may find it easier to access information, material and financial resources, and conform to social norms, thereby increasing their likelihood of adopting DTs [107]. Additionally, larger-scale farming operations, which generate relatively higher incomes, tend to reduce the perceived investment risk for new technologies [108], providing greater capital channels for acquiring DTs and increasing the likelihood of adopting multiple ones [109].

5.2. DTs Adoption Intensity on Economic Benefit

This study demonstrates that the impact of digital technology on enhancing growers' economic benefits has passed a significance test. Growers can boost their economic benefits by adopting DTs, leading to increased yield and quality, reduced labor costs, irrigation water, and pesticide usage. These findings align with existing studies [110,111]. A study indicated that between 2002 and 2020, in China's major grain-producing regions, the utilization of computers in disseminating meteorological data, managing farmer operations, and maintaining records has led to an increase in grain yield [112].

The economic benefits of DTs hinge on their proper and thorough utilization, which cannot be overlooked. Given their inherent complexity and demanding operational requirements, improper handling by farmers can seriously compromise their effectiveness and pose risks of reduced yields [113,114]. However, attributing all errors in the application of DTs to farmers alone would be inappropriate. The limitations and immaturity of the DTs itself should also be taken into account [19].

5.3. Limitation

While this study offers a comprehensive analysis and discussion on the adoption of DTs in cultivation in China, several limitations should be noted. Perhaps the most significant limitation lies in the rapid evolution of the technology itself, coupled with the dynamic nature of growers' adoption of DTs. It is crucial to identify pertinent barriers by assessing state-of-the-art technologies across different developmental stages. This study holds crucial implications for the current promotion of DTs. It is also imperative to conduct a follow-up study, employing a long-term tracking approach, to understand the evolving trends in the adoption and benefits of DTs over time.

6. Conclusions and Policy Implications

This study conducts an in-depth examination of the key factors and application effectiveness of digital technologies (DTs) adoption, using Chinese growers as a case study. Our findings can provide insights for developing countries facing similar challenges in agricultural modernization and digital transformation to advance the application of DTs in agriculture more effectively. In terms of internal factors, the grower's knowledge and technology compatibility play a crucial role in the adoption of DTs. Growers with higher levels of knowledge are more likely to comprehend the functionalities and advantages of DTs, thus increasing their likelihood of adoption. Lower technology compatibility implies that DTs are more suitable for large-scale operations, specific agricultural environments, or crop types, rather than being universally applicable to all growers and agricultural sectors. From an external standpoint, government support and competitive pressure significantly influence DTs adoption. Governments mitigate financial and technological risks by providing infrastructure, advanced equipment, training, and financial support. Competitive pressure, mainly through peer effects, promotes DTs adoption. Additionally, growers' personal and agricultural production characteristics also affect adoption, with male and larger-scale growers showing higher adoption rates. These findings further corroborate that DTs can enhance growers' economic benefits by reducing labor and input costs while simultaneously increasing yields and improving quality. However, such benefits are not always guaranteed and are contingent upon the maturity of DTs and the standardization of growers' practices.

Drawing from the findings of this study, two policy implications emerged. It is recommended that governments bolster agricultural socialized services related to DTs. This includes offering pre-adoption technical consultation and support to growers, guiding them in selecting and implementing appropriate DTs. Post-adoption support should be provided through regular technology updates and maintenance to address any challenges encountered during DTs utilization. Second, DTs promotion should prioritize aligning DTs with the practical needs of agricultural production to facilitate their widespread adoption. This entails tailoring technology research, development, and dissemination to accommodate the diverse requirements of growers, considering elements such as cultivation areas, cultivation modes, and crop types.

Author Contributions: Conceptualization, W.G. and J.Z.; methodology, W.G.; software, W.G. and L.L.; validation, W.G. and L.L.; formal analysis, W.G. and L.L.; investigation, W.G., L.L., X.K. and W.W.; resources, J.Z.; data curation, W.G.; writing—original draft preparation, W.G. and L.L.; writing—review and editing, J.Z.; visualization, W.G.; supervision, J.Z.; project administration, J.Z.; funding acquisition, J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key Research and Development Program of China, grant number 2023YFD2000102 and the Agricultural Science and Technology Innovation Program of the Chinese Academy of Agricultural Sciences, grant number CAAS-ASTIP-2023-AII.

Institutional Review Board Statement: This study is not human or animal research, and no sensitive data were obtained or used. Therefore, it is not necessary to specify an Institutional Review Board Statement.

Informed Consent Statement: Informed consent was obtained from all growers surveyed and interviewed in the study.

Data Availability Statement: Dataset available on request from the corresponding author.

Acknowledgments: The authors are grateful for the patient review and helpful suggestions from the editors of this journal, as well as the anonymous referees.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Survey Questionnaire on Growers' Digital Technology Adoption

Dear growers,

We appreciate your participation in completing the survey. The purpose of this survey is to understand the adoption and application of digital technologies by growers in China. The questionnaire is anonymous and will not disclose your privacy. The data obtained will only be used for academic research. Participation in this study is entirely voluntary, and you have the freedom to decline or withdraw at any time without facing any repercussions. Feel free to raise concerns or questions; we'll address them satisfactorily. The estimated time for completion is about 10 min. We sincerely thank you for your participation!

Table A1. A Survey questionnaire and information.

Part 1. Individual and Agricultural Production Characteristics
1. Sex: 2. Age: 3. Years of education: 4. Geographical location: 5. Ho many years you involved in cultivation: 6. What is the main crop you cultivated: 7. What is the area you cultivation (mu): 8. The fixed laborers you employ: 9. The number of digital technology training sessions attended over the past three years: 10. What is the output value of cultivation over the past three years (yuan/mu/year): 11. What is the total cost of cultivation over the past three years (yuan/mu/year): 12. Over the last three years, has agricultural production and operations been impacted by COVID-19: ○ No impacts ○ Low impacts ○ Moderate impacts ○ High impacts
Part 2. The digital technology adoption status
13. The digital technologies you currently adopted are as follows: ○ Digital sensors ○ Precision irrigation systems ○ Precision fertilization systems ○ Unmanned aerial vehicles 14. The proportion of peers in your county applying digital technologies for agricultural production: 15. Over the next five years, what is the likely trend regarding your adoption of digital technologies: ○ Decrease ○ Maintain status quo ○ Increase ○ Uncertain
Part 3. Influencing factors
16. In terms of factors, please choose the option that best suits you:

Table A1. *Cont.*

Grower's knowledge	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
You have heard about and gained knowledge about these digital technologies.	○	○	○	○	○
You are very familiar with the functionalities and prospects of these digital technologies in the agricultural sector.	○	○	○	○	○
You are willing to undergo training in digital technologies when given the opportunity.	○	○	○	○	○
Technology compatibility	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
The application of digital technologies can solve the difficulties currently faced by your farm.	○	○	○	○	○
Digital technologies can be compatible with your farm's existing software and hardware.	○	○	○	○	○
The application of digital technologies aligns with the organizational culture and value system of your farm.					
Government support	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Your farm's adoption of digital technologies can benefit from government policies and financial support.	○	○	○	○	○
The government supports various agricultural information and digitization projects of your farm.	○	○	○	○	○
The government encourages farms to adopt digital technologies by promoting successful cases and technical training.	○	○	○	○	○
Competitive pressure	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Under competitive pressure, you have no choice but to adopt digital technologies.	○	○	○	○	○
Applying digital technologies can provide you with more competitive advantages.	○	○	○	○	○
If peers or competitors adopt digital technologies, you are also inclined to adopt it.	○	○	○	○	○
The questionnaire concludes here. Thank you once more for your support and cooperation. Wishing you a productive and enjoyable work ahead!					

References

1. Klerkx, L.; Rose, D. Dealing with the Game-Changing Technologies of Agriculture 4.0: How Do We Manage Diversity and Responsibility in Food System Transition Pathways? *Glob. Food Secur.* **2020**, *24*, 100347. [CrossRef]
2. Lezoche, M.; Hernandez, J.E.; Alemany Díaz, M.d.M.E.; Panetto, H.; Kacprzyk, J. Agri-Food 4.0: A Survey of the Supply Chains and Technologies for the Future Agriculture. *Comput. Ind.* **2020**, *117*, 103187. [CrossRef]
3. Gebresenbet, G.; Bosona, T.; Patterson, D.; Persson, H.; Fischer, B.; Mandaluniz, N.; Chirici, G.; Zacepins, A.; Komasilovs, V.; Pitulac, T.; et al. A Concept for Application of Integrated Digital Technologies to Enhance Future Smart Agricultural Systems. *Smart Agric. Technol.* **2023**, *5*, 100255. [CrossRef]
4. Regan, Á. 'Smart Farming' in Ireland: A Risk Perception Study with Key Governance Actors. *NJAS—Wagening. J. Life Sci.* **2019**, *90–91*, 100292. [CrossRef]
5. Rotz, S.; Gravely, E.; Mosby, I.; Duncan, E.; Finnis, E.; Horgan, M.; LeBlanc, J.; Martin, R.; Neufeld, H.T.; Nixon, A.; et al. Automated Pastures and the Digital Divide: How Agricultural Technologies Are Shaping Labour and Rural Communities. *J. Rural Stud.* **2019**, *68*, 112–122. [CrossRef]
6. Kitole, F.A.; Mkuna, E.; Sesabo, J.K. Digitalization and Agricultural Transformation in Developing Countries: Empirical Evidence from Tanzania Agriculture Sector. *Smart Agric. Technol.* **2024**, *7*, 100379. [CrossRef]
7. Carolan, M. Publicising Food: Big Data, Precision Agriculture, and Co-Experimental Techniques of Addition. *Sociol. Rural.* **2017**, *57*, 135–154. [CrossRef]
8. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.-J. Big Data in Smart Farming—A Review. *Agric. Syst.* **2017**, *153*, 69–80. [CrossRef]
9. Lioutas, E.D.; Charatsari, C.; De Rosa, M. Digitalization of Agriculture: A Way to Solve the Food Problem or a Trolley Dilemma? *Technol. Soc.* **2021**, *67*, 101744. [CrossRef]
10. Abiri, R.; Rizan, N.; Balasundram, S.K.; Shahbazi, A.B.; Abdul-Hamid, H. Application of Digital Technologies for Ensuring Agricultural Productivity. *Heliyon* **2023**, *9*, e22601. [CrossRef]
11. McFadden, J. *Precision Agriculture in the Digital Era: Recent Adoption on U.S. Farms*; USDA Economic Research Service: Washington, DC, USA, 2023.

12. Zul Azlan, Z.H.; Junaini, S.N.; Bolhassan, N.A.; Wahi, R.; Arip, M.A. Harvesting a Sustainable Future: An Overview of Smart Agriculture's Role in Social, Economic, and Environmental Sustainability. *J. Clean. Prod.* **2024**, *434*, 140338. [CrossRef]
13. Koutsos, T.; Menexes, G. Economic, Agronomic, and Environmental Benefits from the Adoption of Precision Agriculture Technologies: A Systematic Review. *Int. J. Agric. Environ. Inf. Syst. (IJAEIS)* **2019**, *10*, 40–56. [CrossRef]
14. Wolfert, S.; Isakhanyan, G. Sustainable Agriculture by the Internet of Things—A Practitioner's Approach to Monitor Sustainability Progress. *Comput. Electron. Agric.* **2022**, *200*, 107226. [CrossRef]
15. Kayad, A.; Sozzi, M.; Gatto, S.; Whelan, B.; Sartori, L.; Marinello, F. Ten Years of Corn Yield Dynamics at Field Scale under Digital Agriculture Solutions: A Case Study from North Italy. *Comput. Electron. Agric.* **2021**, *185*, 106126. [CrossRef]
16. Far, S.T.; Rezaei-Moghaddam, K. Impacts of the Precision Agricultural Technologies in Iran: An Analysis Experts' Perception & Their Determinants. *Inf. Process. Agric.* **2018**, *5*, 173–184.
17. Abate, G.T.; Abay, K.A.; Chamberlin, J.; Kassim, Y.; Spielman, D.J.; Tabe-Ojong, M.P., Jr. Digital Tools and Agricultural Market Transformation in Africa: Why Are They Not at Scale yet, and What Will It Take to Get There? *Food Policy* **2023**, *116*, 102439. [CrossRef]
18. Deichmann, U.; Goyal, A.; Mishra, D. Will Digital Technologies Transform Agriculture in Developing Countries? *Agric. Econ.* **2016**, *47*, 21–33. [CrossRef]
19. Visser, O.; Sippel, S.R.; Thiemann, L. Imprecision Farming? Examining the (in)Accuracy and Risks of Digital Agriculture. *J. Rural Stud.* **2021**, *86*, 623–632. [CrossRef]
20. Yi, Y.; Xu, W.; Fan, Y.; Wang, H.-X. Drosophila as an Emerging Model Organism for Studies of Food-Derived Antioxidants. *Food Res. Int.* **2021**, *143*. [CrossRef]
21. Li, L.; Paudel, K.P.; Guo, J. Understanding Chinese Farmers' Participation Behavior Regarding Vegetable Traceability Systems. *Food Control* **2021**, *130*, 108325. [CrossRef]
22. Yang, C.; Ji, X.; Cheng, C.; Liao, S.; Obuobi, B.; Zhang, Y. Digital Economy Empowers Sustainable Agriculture: Implications for Farmers' Adoption of Ecological Agricultural Technologies. *Ecol. Indic.* **2024**, *159*, 111723. [CrossRef]
23. Jiang, K.; Chen, Z.; Rughoo, A.; Zhou, M. Internet Finance and Corporate Investment: Evidence from China. *J. Int. Financ. Mark. Inst. Money* **2022**, *77*, 101535. [CrossRef]
24. Carrer, M.J.; Filho, H.M.d.S.; Vinholis, M.d.M.B.; Mozambani, C.I. Precision Agriculture Adoption and Technical Efficiency: An Analysis of Sugarcane Farms in Brazil. *Technol. Forecast. Soc. Chang.* **2022**, *177*, 121510. [CrossRef]
25. Dressler, M.; Paunovic, I. Sensing Technologies, Roles and Technology Adoption Strategies for Digital Transformation of Grape Harvesting in SME Wineries. *J. Open Innov. Technol. Mark. Complex.* **2021**, *7*, 123. [CrossRef]
26. Allahyari, M.S.; Mohammadzadeh, M.; Nastis, S.A. Agricultural Experts' Attitude towards Precision Agriculture: Evidence from Guilan Agricultural Organization, Northern Iran. *Inf. Process. Agric.* **2016**, *3*, 183–189. [CrossRef]
27. Kolady, D.E.; Van der Sluis, E.; Uddin, M.M.; Deutz, A.P. Determinants of Adoption and Adoption Intensity of Precision Agriculture Technologies: Evidence from South Dakota. *Precis. Agric.* **2021**, *22*, 689–710. [CrossRef]
28. Paudel, K.P.; Mishra, A.K.; Pandit, M.; Larkin, S.; Rejesus, R.; Velandia, M. Modeling Multiple Reasons for Adopting Precision Technologies: Evidence from U.S. Cotton Producers. *Comput. Electron. Agric.* **2020**, *175*, 105625. [CrossRef]
29. Drewry, J.L.; Shutske, J.M.; Trechter, D.; Luck, B.D.; Pitman, L. Assessment of Digital Technology Adoption and Access Barriers among Crop, Dairy and Livestock Producers in Wisconsin. *Comput. Electron. Agric.* **2019**, *165*, 104960. [CrossRef]
30. Michels, M.; von Hobe, C.-F.; Musshoff, O. A Trans-Theoretical Model for the Adoption of Drones by Large-Scale German Farmers. *J. Rural Stud.* **2020**, *75*, 80–88. [CrossRef]
31. Schnebelin, É. Linking the Diversity of Ecologisation Models to Farmers' Digital Use Profiles. *Ecol. Econ.* **2022**, *196*, 107422. [CrossRef]
32. Ammann, J.; Umstaetter, C.; El Benni, N. The Adoption of Precision Agriculture Enabling Technologies in Swiss Outdoor Vegetable Production: A Delphi Study. *Precis. Agric.* **2022**, *23*, 1354–1374. [CrossRef]
33. Fan, X.; Wang, Z.; Wang, Y. Rural Business Environments, Information Channels, and Farmers' Pesticide Utilization Behavior: A Grounded Theory Analysis in Hainan Province, China. *Agriculture* **2024**, *14*, 196. [CrossRef]
34. Ji, J.; Zhuo, K.; Zeng, Y.; Su, J.; Xie, Y. The Impact of Multi-Subjective Governance on Tea Farmers' Green Production Behavior Based on the Improved Theory of Planned Behavior. *Sustainability* **2023**, *15*, 15811. [CrossRef]
35. Creswell, J.D. *Creswell Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*, 5th ed.; SAGE Publications: New York, NY, USA, 2017.
36. Malina, M.A.; Nørreklit, H.S.O.; Selto, F.H. Lessons Learned: Advantages and Disadvantages of Mixed Method Research. *Qual. Res. Account. Manag.* **2011**, *8*, 59–71. [CrossRef]
37. Stathakopoulos, V.; Kottikas, K.G.; Painesis, G.; Theodorakis, I.G.; Kottika, E. Why Shape a Market? Empirical Evidence on the Prominent Firm-Level and Market-Level Outcomes of Market-Driving Strategy. *J. Bus. Res.* **2022**, *139*, 1240–1254. [CrossRef]
38. Kurtaliqi, F.; Lancelot Miltgen, C.; Viglia, G.; Pantin-Sohier, G. Using Advanced Mixed Methods Approaches: Combining PLS-SEM and Qualitative Studies. *J. Bus. Res.* **2024**, *172*, 114464. [CrossRef]
39. Garrido-Moreno, A.; Martín-Rojas, R.; García-Morales, V.J. The Key Role of Innovation and Organizational Resilience in Improving Business Performance: A Mixed-Methods Approach. *Int. J. Inf. Manag.* **2024**, *77*, 102777. [CrossRef]
40. Balogh, P.; Bai, A.; Czibere, I.; Kovach, I.; Fodor, L.; Bujdos, A.; Sulyok, D.; Gabnai, Z.; Birkner, Z. Big Data in Smart Farming—A Review. Agricultural Systems. *Agronomy* **2021**, *11*, 1112. [CrossRef]

41. Wang, Y.; Jin, L.; Mao, H. Farmer Cooperatives' Intention to Adopt Agricultural Information Technology—Mediating Effects of Attitude. *Inf. Syst. Front.* **2019**, *21*, 565–580. [CrossRef]
42. Lin, H.-F.; Lin, S.-M. Determinants of E-Business Diffusion: A Test of the Technology Diffusion Perspective. *Technovation* **2008**, *28*, 135–145. [CrossRef]
43. Yadav, S.; Kaushik, A.; Sharma, M.; Sharma, S. Disruptive Technologies in Smart Farming: An Expanded View with Sentiment Analysis. *AgriEngineering* **2022**, *4*, 424–460. [CrossRef]
44. Annosi, M.C.; Brunetta, F.; Monti, A.; Nati, F. Is the Trend Your Friend? An Analysis of Technology 4.0 Investment Decisions in Agricultural SMEs. *Comput. Ind.* **2019**, *109*, 59–71. [CrossRef]
45. Shi, P.; Yan, B. Factors Affecting RFID Adoption in the Agricultural Product Distribution Industry: Empirical Evidence from China. *SpringerPlus* **2016**, *5*, 2029. [CrossRef]
46. Wang, Y.-M.; Wang, Y.-S.; Yang, Y.-F. Understanding the Determinants of RFID Adoption in the Manufacturing Industry. *Technol. Forecast. Soc. Chang.* **2010**, *77*, 803–815. [CrossRef]
47. Yoon, C.; Lim, D.; Park, C. Factors Affecting Adoption of Smart Farms: The Case of Korea. *Comput. Hum. Behav.* **2020**, *108*, 106309. [CrossRef]
48. Kuan, K.K.Y.; Chau, P.Y.K. A Perception-Based Model for EDI Adoption in Small Businesses Using a Technology-Organization-Environment Framework. *Inf. Manag.* **2001**, *38*, 507–521. [CrossRef]
49. Dixit, K.; Aashish, K.; Kumar Dwivedi, A. Antecedents of Smart Farming Adoption to Mitigate the Digital Divide—Extended Innovation Diffusion Model. *Technol. Soc.* **2023**, *75*, 102348. [CrossRef]
50. Low, C.; Chen, Y.; Wu, M. Understanding the Determinants of Cloud Computing Adoption. *Ind. Manag. Data Syst.* **2011**, *111*, 1006–1023. [CrossRef]
51. Wei, J.; Lowry, P.B.; Seedorf, S. The Assimilation of RFID Technology by Chinese Companies: A Technology Diffusion Perspective. *Inf. Manag.* **2015**, *52*, 628–642. [CrossRef]
52. de Prieelle, F.; de Reuver, M.; Rezaei, J. The Role of Ecosystem Data Governance in Adoption of Data Platforms by Internet-of-Things Data Providers: Case of Dutch Horticulture Industry. *IEEE Trans. Eng. Manag.* **2022**, *69*, 940–950. [CrossRef]
53. Garbach, K.; Lubell, M.; DeClerck, F.A.J. Payment for Ecosystem Services: The Roles of Positive Incentives and Information Sharing in Stimulating Adoption of Silvopastoral Conservation Practices. *Agric. Ecosyst. Environ.* **2012**, *156*, 27–36. [CrossRef]
54. Piñeiro, V.; Arias, J.; Dürr, J.; Elverdin, P.; Ibáñez, A.M.; Kinengyere, A.; Opazo, C.M.; Owoo, N.; Page, J.R.; Prager, S.D.; et al. A Scoping Review on Incentives for Adoption of Sustainable Agricultural Practices and Their Outcomes. *Nat. Sustain.* **2020**, *3*, 809–820. [CrossRef]
55. Bahn, R.A.; Yehya, A.A.K.; Zurayk, R. Digitalization for Sustainable Agri-Food Systems: Potential, Status, and Risks for the MENA Region. *Sustainability* **2021**, *13*, 3223. [CrossRef]
56. Schimmelpfennig, D. (Ed.) *Farm Profits and Adoption of Precision Agriculture*; Economic Research Report; USDA: Washington, DC, USA, 2016.
57. Erdem, M.; Ağır, H.B. Enhancing Dairy Farm Welfare: A Holistic Examination of Technology Adoption and Economic Performance in Kahramanmaraş Province, Turkey. *Sustainability* **2024**, *16*, 2989. [CrossRef]
58. Prause, L.; Hackfort, S.; Lindgren, M. Digitalization and the Third Food Regime. *Agric. Hum. Values* **2021**, *38*, 641–655. [CrossRef]
59. Boursianis, A.D.; Papadopoulou, M.S.; Diamantoulakis, P.; Liopa-Tsakalidi, A.; Barouchas, P.; Salahas, G.; Karagiannidis, G.; Wan, S.; Goudos, S.K. Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in Smart Farming: A Comprehensive Review. *Internet Things* **2022**, *18*, 100187. [CrossRef]
60. Kakkavou, K.; Gemtou, M.; Fountas, S. Drivers and Barriers to the Adoption of Precision Irrigation Technologies in Olive and Cotton Farming—Lessons from Messenia and Thessaly Regions in Greece. *Smart Agric. Technol.* **2024**, *7*, 100401. [CrossRef]
61. Chen, C.; Pan, J.; Lam, S.K. A Review of Precision Fertilization Research. *Environ. Earth Sci* **2014**, *71*, 4073–4080. [CrossRef]
62. Friha, O.; Ferrag, M.A.; Shu, L.; Maglaras, L.; Wang, X. Internet of Things for the Future of Smart Agriculture: A Comprehensive Survey of Emerging Technologies. *IEEE/CAA J. Autom. Sin.* **2021**, *8*, 718–752. [CrossRef]
63. Isgin, T.; Bilgic, A.; Forster, D.L.; Batte, M.T. Using Count Data Models to Determine the Factors Affecting Farmers' Quantity Decisions of Precision Farming Technology Adoption. *Comput. Electron. Agric.* **2008**, *62*, 231–242. [CrossRef]
64. Tiago, O. Assessing the Determinants of Cloud Computing Adoption: An Analysis of the Manufacturing and Services Sectors. *Inf. Manag.* **2014**, *51*, 497–510.
65. Junior, C.H.; Oliveira, T.; Yanaze, M. The Adoption Stages (Evaluation, Adoption, and Routinisation) of ERP Systems with Business Analytics Functionality in the Context of Farms. *Comput. Electron. Agric.* **2019**, *156*, 334–348. [CrossRef]
66. Aubert, B.A.; Schroeder, A.; Grimaudo, J. IT as Enabler of Sustainable Farming: An Empirical Analysis of Farmers' Adoption Decision of Precision Agriculture Technology. *Decis. Support Syst.* **2012**, *54*, 510–520. [CrossRef]
67. Balogh, P.; Bai, A.; Czibere, I.; Kovách, I.; Fodor, L.; Bujdos, Á.; Sulyok, D.; Gabnai, Z.; Birkner, Z. Economic and Social Barriers of Precision Farming in Hungary. *Agronomy* **2021**, *11*, 1112. [CrossRef]
68. Carrer, M.J.; de Souza Filho, H.M.; Batalha, M.O. Factors Influencing the Adoption of Farm Management Information Systems (FMIS) by Brazilian Citrus Farmers. *Comput. Electron. Agric.* **2017**, *138*, 11–19. [CrossRef]
69. Ofori, E.; Griffin, T.; Yeager, E. Balogh. *Agric. Financ. Rev.* **2020**, *80*, 647–664. [CrossRef]
70. Pierpaoli, E.; Carli, G.; Pignatti, E.; Canavari, M. Drivers of Precision Agriculture Technologies Adoption: A Literature Review. *Procedia Technol.* **2013**, *8*, 61–69. [CrossRef]

71. Sridhar, A.; Balakrishnan, A.; Jacob, M.M.; Sillanpää, M.; Dayanandan, N. Global Impact of COVID-19 on Agriculture: Role of Sustainable Agriculture and Digital Farming. *Environ. Sci. Pollut. Res.* **2023**, *30*, 42509–42525. [CrossRef]
72. Li, W.; Wang, F.; Liu, T.; Xue, Q.; Liu, N. Peer Effects of Digital Innovation Behavior: An External Environment Perspective. *Manag. Decis.* **2023**, *61*, 2173–2200. [CrossRef]
73. An, W.H. Instrumental Variables Estimates of Peer Effects in Social Networks. *Soc. Sci. Res.* **2015**, *50*, 382–394. [CrossRef]
74. Chernozhukov, V.; Hansen, C. Instrumental Variable Quantile Regression: A Robust Inference Approach. *Rodríguez* **2008**, *142*, 379–398. [CrossRef]
75. Niu, Z.; Chen, C.; Gao, Y.; Wang, Y.; Chen, Y.; Zhao, K. Peer Effects, Attention Allocation and Farmers' Adoption of Cleaner Production Technology: Taking Green Control Techniques as an Example. *J. Clean. Prod.* **2022**, *339*, 130700. [CrossRef]
76. Fávero, L.P.; Belfiore, P. Chapter 15—Regression Models for Count Data: Poisson and Negative Binomial. In *Data Science for Business and Decision Making*; Fávero, L.P., Belfiore, P., Eds.; Academic Press: Cambridge, MA, USA, 2019; pp. 617–703, ISBN 978-0-12-811216-8.
77. Cameron, A.C.; Trivedi, P.K. Regression-Based Tests for Overdispersion in the Poisson Model. *J. Econ.* **1990**, *46*, 347–364. [CrossRef]
78. Lawless, J.F. Negative Binomial and Mixed Poisson Regression. *Can. J. Stat.* **1987**, *15*, 209–225. [CrossRef]
79. Yao, J.; Wang, D. The Impact of Analyst Attention on the Firms' Innovation Paths from a Life Cycle Perspective: Evidence from China. *Heliyon* **2023**, *9*, e18940. [CrossRef]
80. Cronbach, L.J. Coefficient Alpha and the Internal Structure of Tests. *Psychometrika* **1951**, *16*, 297–334. [CrossRef]
81. Bartlett, M.S. Tests of Significance in Factor Analysis. *Br. J. Stat. Psychol.* **1950**, *3*, 77–85. [CrossRef]
82. Kaiser, H.F. An Index of Factorial Simplicity. *Psychometrika* **1974**, *39*, 31–36. [CrossRef]
83. Leguina, A. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). *Int. J. Res. Method Educ.* **2015**, *38*, 220–221. [CrossRef]
84. de Jongh, P.; de Jongh, E.; Pienaar, M.; Gordon-Grant, H.; Oberholzer, M.; Santana, L. The Impact of Pre-Selected Variance Inflation Factor Thresholds on the Stability and Predictive Power of Logistic Regression Models in Credit Scoring. *ORiON* **2015**, *31*, 17–37. [CrossRef]
85. Staffini, A.; Fujita, K.; Svensson, A.K.; Chung, U.-I.; Svensson, T. Statistical Methods for Item Reduction in a Representative Lifestyle Questionnaire: Pilot Questionnaire Study. *Interact. J. Med. Res.* **2022**, *11*, e28692. [CrossRef]
86. Oster, E. Unobservable Selection and Coefficient Stability: Theory and Evidence. *J. Bus. Econ. Stat.* **2019**, *37*, 187–204. [CrossRef]
87. Zeidan, R.; Van Holt, T.; Whelan, T. Existence Inductive Theory Building to Study Coordination Failures in Sustainable Beef Production. *J. Clean. Prod.* **2020**, *267*, 122137. [CrossRef]
88. Byrne, D. A Worked Example of Braun and Clarke's Approach to Reflexive Thematic Analysis. *Qual. Quant.* **2022**, *56*, 1391–1412. [CrossRef]
89. Hansen, B.D.; Leonard, E.; Mitchell, M.C.; Easton, J.; Shariati, N.; Mortlock, M.Y.; Schaefer, M.; Lamb, D.W. Current Status of and Future Opportunities for Digital Agriculture in Australia. *Crop Pasture Sci.* **2022**, *74*, 524–537. [CrossRef]
90. Lin, D.; Lee, C.K.M.; Lin, K. Research on Effect Factors Evaluation of Internet of Things (IOT) Adoption in Chinese Agricultural Supply Chain. In Proceedings of the 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali, Indonesia, 4–6 December 2016; pp. 612–615.
91. Marra, M.; Pannell, D.J.; Abadi Ghadim, A. The Economics of Risk, Uncertainty and Learning in the Adoption of New Agricultural Technologies: Where Are We on the Learning Curve? *Agric. Syst.* **2003**, *75*, 215–234. [CrossRef]
92. Carolan, M. Digitization as Politics: Smart Farming through the Lens of Weak and Strong Data. *J. Rural Stud.* **2022**, *91*, 208–216. [CrossRef]
93. Gerli, P.; Clement, J.; Esposito, G.; Mora, L.; Crutzen, N. The Hidden Power of Emotions: How Psychological Factors Influence Skill Development in Smart Technology Adoption. *Technol. Forecast. Soc. Chang.* **2022**, *180*, 121721. [CrossRef]
94. Abdollahzadeh, G.; Damalas, C.A.; Sharifzadeh, M.S.; Ahmadi-Gorgi, H. Selecting Strategies for Rice Stem Borer Management Using the Analytic Hierarchy Process (AHP). *Crop Prot.* **2016**, *84*, 27–36. [CrossRef]
95. Rezaei, R.; Safa, L.; Ganjkhanloo, M.M. Understanding Farmers' Ecological Conservation Behavior Regarding the Use of Integrated Pest Management—An Application of the Technology Acceptance Model. *Glob. Ecol. Conserv.* **2020**, *22*, e00941. [CrossRef]
96. Oyibo, K.; Morita, P.P. COVID Alert: Factors Influencing the Adoption of Exposure Notification Apps Among Canadian Residents. *Front. Digit. Health* **2022**, *4*, 842661. [CrossRef]
97. Scur, G.; da Silva, A.V.D.; Mattos, C.A.; Gonçalves, R.F. Analysis of IoT Adoption for Vegetable Crop Cultivation: Multiple Case Studies. *Technol. Forecast. Soc. Chang.* **2023**, *191*, 122452. [CrossRef]
98. Rose, D.C.; Sutherland, W.J.; Parker, C.; Lobley, M.; Winter, M.; Morris, C.; Twining, S.; Ffoulkes, C.; Amano, T.; Dicks, L.V. Decision Support Tools for Agriculture: Towards Effective Design and Delivery. *Agric. Syst.* **2016**, *149*, 165–174. [CrossRef]
99. Sun, S.; Cegielski, C.G.; Jia, L.; Hall, D.J. Understanding the Factors Affecting the Organizational Adoption of Big Data. *J. Comput. Inf. Syst.* **2018**, *58*, 193–203. [CrossRef]
100. Taheri, F.; D'Haese, M.; Fiems, D.; Azadi, H. The Intentions of Agricultural Professionals towards Diffusing Wireless Sensor Networks: Application of Technology Acceptance Model in Southwest Iran. *Technol. Forecast. Soc. Chang.* **2022**, *185*, 122075. [CrossRef]

101. Lee, C.-L.; Strong, R.; Dooley, K.E. Analyzing Precision Agriculture Adoption across the Globe: A Systematic Review of Scholarship from 1999–2020. *Sustainability* **2021**, *13*, 10295. [CrossRef]
102. Shang, L.; Heckelei, T.; Gerullis, M.K.; Börner, J.; Rasch, S. Adoption and Diffusion of Digital Farming Technologies—Integrating Farm-Level Evidence and System Interaction. *Agric. Syst.* **2021**, *190*, 103074. [CrossRef]
103. Malik, S.; Chadhar, M.; Chetty, M.; Vatanasakdakul, S. Adoption of Blockchain Technology: Exploring the Factors Affecting Organizational Decision. *Hum. Behav. Emerg. Technol.* **2022**, *2022*, 1–14. [CrossRef]
104. Zhu, K.; Kraemer, K.L.; Xu, S. The Process of Innovation Assimilation by Firms in Different Countries: A Technology Diffusion Perspective on E-Business. *Manag. Sci.* **2006**, *52*, 1557–1576. [CrossRef]
105. Krishnan, P.; Patnam, M. Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption? *Am. J. Agric. Econ.* **2014**, *96*, 308–327. [CrossRef]
106. Ferrali, R.; Grossman, G.; Platas, M.R.; Rodden, J. It Takes a Village: Peer Effects and Externalities in Technology Adoption. *Am. J. Political Sci.* **2020**, *64*, 536–553. [CrossRef]
107. Aparo, N.O.; Odongo, W.; De Steur, H. Unraveling Heterogeneity in Farmer's Adoption of Mobile Phone Technologies: A Systematic Review. *Technol. Forecast. Soc. Chang.* **2022**, *185*, 122048. [CrossRef]
108. Barnes, A.P.; Soto, I.; Eory, V.; Beck, B.; Balafoutis, A.; Sánchez, B.; Vangeyte, J.; Fountas, S.; van der Wal, T.; Gómez-Barbero, M. Exploring the Adoption of Precision Agricultural Technologies: A Cross Regional Study of EU Farmers. *Land Use Policy* **2019**, *80*, 163–174. [CrossRef]
109. Tamirat, T.W.; Pedersen, S.M.; Lind, K.M. Farm and Operator Characteristics Affecting Adoption of Precision Agriculture in Denmark and Germany. *Acta Agric. Scand. Sect. B—Soil Plant Sci.* **2018**, *68*, 349–357. [CrossRef]
110. Weltin, M.; Zasada, I.; Hüttel, S. Relevance of Portfolio Effects in Adopting Sustainable Farming Practices. *J. Clean. Prod.* **2021**, *313*, 127809. [CrossRef]
111. Symeonaki, E.; Arvanitis, K.; Piromalis, D. A Context-Aware Middleware Cloud Approach for Integrating Precision Farming Facilities into the IoT toward Agriculture 4.0. *Appl. Sci.* **2020**, *10*, 813. [CrossRef]
112. Chandio, A.A.; Ozdemir, D.; Gokmenoglu, K.K.; Usman, M.; Jiang, Y. Digital Agriculture for Sustainable Development in China: The Promise of Computerization. *Technol. Soc.* **2024**, *76*, 102479. [CrossRef]
113. Chinseu, E.; Dougill, A.; Stringer, L. Why Do Smallholder Farmers Dis-adopt Conservation Agriculture? Insights from Malawi. *Land Degrad. Dev.* **2019**, *30*, 533–543. [CrossRef]
114. Trujillo-Barrera, A.; Pennings, J.M.E.; Hofenk, D. Understanding Producers' Motives for Adopting Sustainable Practices: The Role of Expected Rewards, Risk Perception and Risk Tolerance. *Eur. Rev. Agric. Econ.* **2016**, *43*, 359–382. [CrossRef]