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THE DIGITAL AGRICULTURE MODEL FOR SUSTAINABLE FOOD SYSTEM: AN ANALYSIS OF AGRICULTURAL TECHNOLOGY ADOPTION IN EAST JAVA, INDONESIA

BUNGA HIDAYATI[1,2]*, ERMITA YUSIDA[3], VIKA ANNISA QURRATA[3], NASIKH[3] AND WEN-CHI HUANG[4]

[1]*Department of Economics, Faculty of Economics and Business, Universitas Brawijaya, Malang, Indonesia.* [2]*Postgraduate School of Universitas Brawijaya, Jalan MT. Haryono 165, Malang, 65145 Kota Malang, Jawa Timur, Indonesia.* [3]*Department of Economic Development, Faculty of Economics and Business, Universitas Negeri Malang Jl. Semarang No. 5,65145, Malang, Jawa Timur, Indonesia.* [4]*National Pingtung University of Science and Technology. Shuefu Road, Neipu,* Pingtung *91201, Taiwan.*

**Corresponding author: bungahidayati@ub.ac.id*
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Abstract: The agricultural sector plays a crucial role in ensuring national food security. Sustainable agriculture can be a major contributor towards this end, as well as towards future national development. However, the success of digital agriculture initiatives depends on farmers' technological literacy. Farmer regeneration and human resources are among the major challenges faced by farmers in Indonesia. This study aims to analyse farmers' knowledge, behaviour and preferences for adoptinf technology, such as soil fertiliser technology, water-saving irrigation technology, green technology, and digital marketing technology. This study employs a quantitative approach using Warp-PLS 6.0 structural equation model method. The results indicate that farmers currently prefer to adopt green technology and digital marketing technology, as they are reinforced by bother farmer knowledge and behaviour. However, farmers' preferences for adopting soil fertiliser technology and water-saving technology are only influenced by their knowledge and not their behaviour.

Keywords: Digital agriculture, sustainable food system, technology adoption, structural equation model.

Introduction

The increasing population growth in Indonesia poses a major challenge to the national food security system. The increase in population growth must be balanced with the availability of sufficient food to maintain food security stability and avoid relying on imports. Dependence on food imports can have negative consequences on future food security. This is reflected in the Global Food Security Index (GFSI) data from the Economic Intelligence Unit that shows Indonesia ranks third-lowest in Southeast Asia (The Economist Impact, 2021) in terms of food security.

In the Industrial Revolution 4.0 era, integrating agriculture into digital technology systems presents a viable solution to promote and enhance the food security system. One of the functions of digital agriculture is to facilitate access to farmers in overseeing the entire agricultural process, including production and all economic activities. The integration of digital technology in agriculture aligns with the Regional Government Work Plan in East Java for 2021, which aims to improve food security and enhance the competitiveness of potential agricultural product development commodities through the modernization of agricultural infrastructure (East Java Statistical Book, 2021). However, digital agriculture may face obstacles due to low levels of technology literacy among farmers, which can be attributed to the lack of education among farmers.

Sustainable agriculture is one of the implementations of sustainable development. Sustainable development is an effort to harmonise, integrate, and give equal weight to the economic, social, cultural, and environmental aspects. The development of the agricultural sector has a high multiplier effect of stimulating economic growth (Loizou *et al*., 2019). In maintaining the sustainability of farming, it is necessary to introduce technology, where agricultural technology is an essential means of accelerating the transformation of agricultural science and technology achievement and encouraging agricultural modernisation development (Yin *et al*., 2018). Technology extension agriculture involves technical information, solving farmers' technical problems online, and providing agricultural technology support through new media, farm technology and mobile phone applications (Li *et al.,* 2018). In many cases, innovative technologies play an essential role in developing sustainable agricultural systems, which promise to increase food security (Diagne & Cabral, 2017).

The concept of sustainable food production is formed from three critical pillars, consisting of science and technology, social and economic factors, and the environment Socioeconomic instruments include producers, consumers, farmers, markets, and institutions. Meanwhile, environmental tools include land, water, climate, and biodiversity. At the same time, the components of science and technology aim to increase agricultural yields and improve the management of agricultural products. One form of technology used is digital technology, which leads to a positive transformation in the farming sector, changing agriculture and agribusiness in developing countries (Nielson *et al*., 2018).

A more modern digitalisation of agriculture uses agricultural technology systems with sensors to collect data and intelligent machines to retrieve data (Poppe *et al*., 2015). This agrarian technology leads to the concept of smart farming (Sonka, 2015). Supporting similar research on the idea of intelligent farming (Macnaghten *et al.*, 2015), the description of the future of digital agriculture is called "master narratives", which prioritise maximising food yields through technology. The concept of intelligent farming includes soil testing and fertilisation technologies (soil testing and fertilisation technologies), water-saving irrigation technology, and pest control technology, digital technology (Yin *et al*., 2018).

On the other hand, studies on technology adoption in developing countries show that the main barriers hindering adoption are access to technology and a lack of financial services (Alwang *et al*., 2019). In addition, another factor influencing the adoption rate is the specific characteristics of the household, such as age, gender, household size, and farmers' education level (Mwangi & Kariuki, 2015; Theis *et al*., 2018). The latest research on the adoption of agricultural technology conducted in China showed that the results of agricultural technology extension with a new model could increase the technology adoption rate among farmers to some extent with partial effects, and farmers of different ages and with varying sizes of farmland obtain other benefits as well (Gao *et al*., 2020).

The endogenous growth theory forms the basis of character strengths, namely, personal resources, which are expected to influence the decision to adopt technological innovations (S. Bukchin & Kerret, 2018). Apart from the potential of exploiting the character of farmers for sustainable technology implementation, researchers and practitioners usually focus on character deficiencies and barriers (Cafer & Rikoon, 2018). Each farmer possesses a unique set of characteristics that influences their approach to applying natural resources in agriculture. These individual traits, such as creativity, curiosity, courage, justice, self-regulation, and judgment, can greatly impact the overall effectiveness of their agricultural practices (Shira Bukchin & Dorit, 2020).

Several areas in East Java still have food insecure areas (East Java Government, 2021). The inequality of food distribution that occurs in East Java makes it necessary to analyse its relationship further with the behaviour patterns of farmers in areas with high production and low production. In addition, the Agricultural Area Masterplan of East Java Province Based on Farmers' Corporations for 2020-2024 was compiled based on East Java Governor Regulation Number 31 of 2020. This plan aims to develop East Java's agricultural potential and is therefore relevant to the formulation of a digital technology approach model for farmers in the region. (East Java Government, 2021). Therefore, it is necessary to conduct a more in-depth study to formulate a digital technology approach model for farmers in East Java.

Previous studies have discussed more technology at the boundaries of the production process and the role of digital technology, which is described qualitatively. There is a gap theory, based on the "social learning" theory pioneered by Bandura (1977), which explains that individuals can achieve symbolic images of activities that serve as guides in carrying out appropriate actions. In the context of farmers' attitudes towards technological innovation, it can be influenced by natural environmental conditions or agro-ecosystem.

Meanwhile, the "theory of planned behaviour" pioneered by Ajzen (1991) explains that a person's behaviour arises from the intention to behave, which is called perceived behaviour control. Social and institutional conditions greatly influence technology adoption. This means it is important to consider local wisdom and its application when introducing and training new agricultural technologies. This approach can increase community participation and the adoption of mechanisation in the farming process. (Kuntariningsih, 2014).

Based on the two theories, there is a gap that farmers adopting technology can be influenced by natural environmental factors, agro-ecosystems or local wisdom (institutional). The novelty of this research lies in the development of a model that encompasses both the knowledge and behavior aspects of farmers in adopting technology, with a focus on environmental and institutional factors. The ultimate goal is to increase farmers' efficiency through technology adoption. The resulting agriculture model for the future can serve as a reference for policymakers to formulate effective subsidies and technology policies.

Materials and Methods

The study was conducted using a quantitative approach with the use of the structural equation modelling (SEM) as the prime method of analysis SEM is a set of techniques for evaluating latent relationships among multifaceted variables (Bunkus *et al.,* 2020). It works based on hypotheses representing the means, variances, and covariance of empirical data concerning a smaller number of 'structural' factors distinct by a hypothesized underlying theoretical or hypothetical framework. It is a combined approach of factor analysis and multivariate regression that can be used to evaluate the structural connection between latent and measured paradigms or variables (Bradshaw & Minin, 2019). The data was evaluated using the Warp-PLS 6.0 SEM (Structural Equation Model) software.

Data Collection

The data collection of this study was conducted through offline surveys and direct interviews. The study sampled farmers from four districts in East Java Province, namely Banyuwangi, Mojokerto, Malang City, and Batu City, with the selection criteria being farmers who were knowledgeable about or had implemented mechanisation during the harvest process. The sample size was determined using Slovin's formula (Solimun, 2017):

$n = N/(1+N.e^2)$
$n = 107/ (1+107.0.05^2)$
$n = 84,5$
Information:
n = sample size
N = total population
e = error that can be tolerated (error tolerance)

Out of the total population of 107 farmers in the four study areas, 85 usable questionnaires were collected and used in the analysis, with a confidence level of 95% and a significance level of 5%. Most farmers in East Java primarily depend on agriculture for their livelihood, with only a minority (20%) having other jobs as laborers, civil servants, or agricultural extension workers. Despite this, a considerable number of farmers are well-educated, with 25% having completed undergraduate education. However, adoption of digital technology in agriculture remains low, with only 20% of the 85 respondents expressing interest in adopting digital-based agricultural technology and the majority choosing to rarely or not adopt such technology due to its high cost. The study found that 95% of the respondents relied solely on private funds for initial capital and business development, while the rest mainly relied on joining farmers' groups banks for support.

Measurement and Concept of Model

To assess the constructs in the research model, the researchers utilised measurements based on previous studies that had established reliability and validity. Specifically, the measurements for the relative advantage, complexity, and compatibility constructs of the technological dimension were adapted from a study by Oliveira *et al*. (2014). All items were evaluated using a five-point Likert scale, with responses ranging from "strongly disagree" to "strongly agree". The conceptual framework included a specific construct number for all unobserved indicators. In this study, hypothesis testing was conducted using the Warp-PLS 6.0 SEM (Structural Equation Model) software. The study utilized a specific conceptual framework consisting of exogenous latent variables and their manifest variables, which are described in Table 1. Additionally, Table 2 displays the endogenous latent variable and its manifest variables. Figure 1 presents the appropriate structural model for this research.

The SEM approach of partial least squares (PLS) was used to validate the research model. PLS is a component-based approach for estimation and places minimal restrictions on sample size and residual distributions. It is also best suited for analysing complex models with latent variables (Pavlou *et al*., 2007).

Results and Discussion

Description of Technology Adoption by Farmer

Soil Fertiliser Technology

In terms of soil fertiliser technology adoption, only 14% of farmers have chosen to use this digital technology to increase productivity, with 51% of them have adopted it, while the rest choose to adopt it rarely or sometimes. There are several factors that influence farmers' choices in soil fertiliser technology, including the use of new superior varieties, location-specific fertilisation, balanced use of inorganic and organic fertilisers, soil fertility testing, conservation technology for land, and autonomous technologies such as tractors, fertiliser scattering drones, seed scattering drones, and robots. Further analysis of the methods used in soil fertiliser technology revealed that 29% of farmers chose to use new superior varieties and location-specific balanced fertilisation technology, while 9% chose to use location-specific nutrient fertilizers. The use of other digital technologies was also observed, with minor use of soil conservation technologies.

Water-saving Irrigation Technology

The second type of digital technology is water-saving irrigation technology. Water-efficient irrigation can increase irrigation sailing, the planting index, and the planted area to increase agricultural production. However, the development of water-efficient irrigation is hindered by various management issues, including the maintenance of water infrastructure buildings and water resources, and the problem of water utilisation and distribution. Water-efficient irrigation technology is based on the principle of providing irrigation based on the minimum water requirement of the soil. As a result, plants are irrigated with only the minimum amount of water they need, which is lower than their usual requirements. The development of water-efficient irrigation technology faces challenges related to cross-regional water sources, which require appropriate solutions. Additionally,

Table 1: Exogenous latent variable and manifest variable

ST	Soil Fertiliser Technology	WT	Water-saving Technology	GT	Green Technology	MT	Digital Marketing Technology
S1	New superior varieties	W1	Drip irrigation technology	G1	Use of organic fertiliser	D1	Marketing agricultural products through social media
S2	Site-specific nutrient fertilisation	W2	Water harvesting	G2	Waste-free livestock crop integration system	D2	Monitoring prices of agricultural products
S3	Balanced fertilisation technology	W3	Pipeline irrigation network technology	G3	Integrated OPT (plant-disturbing organisms) control	D3	Sales of agricultural products through an online shop platform
S4	Soil test technology	W4	Automatic irrigation system technology	G4	Diversify crops	D4	Funding through the platform
S5	Soil conservation technology					D5	Purchase agricultural equipment and needs through mass media or online
S6	Autonomous tractor technology					D6	Consultations with experts online
						D7	Selling agricultural products to middlemen
						D8	Use of computers/ laptops to access information related to agriculture

Table 2: Endogenous latent variables and manifestations

KT	Farmer knowledge	BR	Farmer behaviour
K1	Knowledge of agricultural innovation	B1	Greenhouse
K2	Knowledge of agriculture technology	B2	Manufacture of organic fertiliser
K3	Government programmes related to agricultural development	B3	Product packaging variations
K4	Access to information increases agricultural productivity	B4	Product agriculture processing
K5	Adopt advanced technology with high cost	B5	Integrated crop management field training
K6	Knowledge of innovation for both production and sales	B6	Integrated pest control field training
K7	Participation in agricultural training		
K8	The use of technology using smartphones, agricultural fertilisers, planting technology		
K9	Knowledge of technology use		

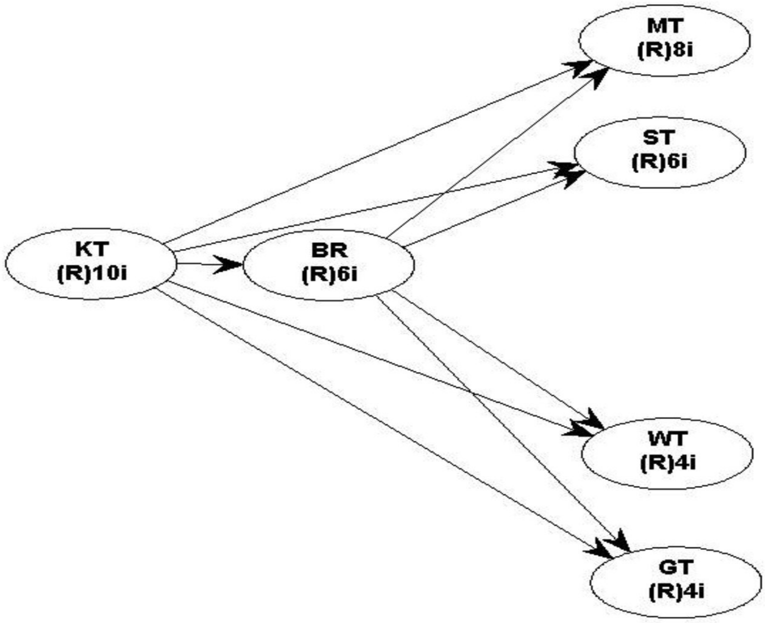

Figure 1: Structural model of farmer's technology adoption

Description:

1. Direct Effect
   KT (Farmer knowledge) → MT (Digital marketing technology)
   KT (Farmer knowledge) → ST (Soil fertiliser technology)
   KT (Farmer knowledge) → WT (Water-saving technology)
   KT (Farmer knowledge) → GT (Green technology)
2. Indirect Effect
   KT (Farmer knowledge) → BR (Farmer behaviour) → MT (Digital marketing technology)
   KT (Farmer knowledge) → BR (Farmer behaviour) → ST (Soil fertiliser technology)
   KT (Farmer knowledge) → BR (Farmer behaviour) → WT (Water-saving technology)
   KT (Farmer knowledge) → BR (Farmer behaviour) → GT (Green technology)

maintenance of water infrastructure buildings and resources necessitates mutual attention. Therefore, establishing new farmer institutions to regulate irrigation water use, maintain water infrastructure and resources, and prevent conflicts of water use during crop production is necessary. As for the adoption of water-saving irrigation technology, only 19.7% of farmers often or very often use it, while 65% choose not to use it. Water-saving irrigation technology that is widely used includes water harvesting through infiltration channels, vertical mulch, reservoirs, intermittent irrigation, and drainage systems. Drip and automatic irrigation are used by at least 4% of farmers.

Green Technology

In the realm of agriculture technology, digitalization has enabled the use of fertilisers as a means of enhancing crop productivity. Digitization through fertiliser aims to control soil fertility levels with the help of organic and inorganic fertilisers. In the era of green technology, fertilisation is based on increasing the energy mix of new and renewable energy by 10 GW, consisting of 6 GW of gas-based energy, 3 GW of renewable energy, and 1 GW of new energy, in which includes hydrogen. The success of increasing the productivity of food crops followed by environmental sustainability is the principle of applying a sustainable, environmentally friendly agricultural system.

This initiative aims to increase the productivity of food crops while promoting environmental sustainability through the application of a sustainable and eco-friendly agricultural system.

To achieve this goal, various ecologically-friendly farming systems have been developed based on good agricultural practices that synergize technological components such as integrated crop management, waste-free crop-livestock integration systems, and integrated pest management. The integration of these technologies promotes food crop productivity, maintains soil quality, and reduces greenhouse gas emissions, all while ensuring the sustainability of the agricultural system. The choice of farmers in East Java in the use of green technology can be represented by 41.76%, which is an excellent result compared to previous agricultural technologies.

This can be attributed to the fact that farmers have widely adopted environmentally friendly farming systems without even realizing it. They undertake various ecologically friendly agricultural operational activities, such as (i) using highly efficient inorganic fertilisers to achieve optimal yield targets; (ii) applying pest and disease control while paying attention to the natural ecological balance; (iii) utilising integrated crop management; (iv) practising clean and healthy farming systems; (v) maintaining and stabilising physical, chemical, and biological fertility of the soil; and, (vi) effectively using technology based on local wisdom.

Digital Marketing Technology

One of the forms of agricultural digitalisation measured in this study is the sales or purchases of farmers through digital marketing technology. The agricultural product marketing system often faces inefficiencies due to weak infrastructure and market information, relatively small agricultural scale, lack of knowledge from marketers on grading and handling, high transaction costs, and lack of good marketing policies. To overcome these issues, farmers must be aware of the agricultural product marketing system from the procurement of raw materials (inputs) to the marketing of farm products.

In addition, online marketing (digital marketing) can be used as an alternative to convey information on developments in agriculture. It can create a more effective and efficient sales system, but only 15% of farmers use digital marketing technology, while 66.45% do not. The majority of farmers still sell agricultural products to middlemen (67%), and 85 respondents still do not use agricultural platforms for sales. Only 2% of farmers buy farm equipment and necessities through mass media or online. Given these findings, researchers must provide socialisation and assistance in handling and packaging agricultural products to increase their added value and selling prices. Farmers should also be equipped with online agricultural product marketing activities, such as selling online on social media, to increase efficiency and effectiveness.

Analysis Data

The PLS-SEM model consists of two-phase analytical approaches, i.e. measurement (outer component) and structural model (inner part). The measurement frameworks provide the multidirectional statistical association for each endogenous structure and its observed response variable. PLS-SEM is capable of handling either formative or reflective measuring styles. Reflective measures are employed to represent the inherent properties of the structure and changes within the structural model, which are indicated by variations in the predictor (transcend) parameters. The reflective indicators in this study were represented by single-headed arrows pointing from the latent construct to the indicator variables. The coefficients associated with these relationships are known as external loads in PLS-SEM. This study utilised reflective measurement models. In contrast, formative indicators are believed to form or shape a latent variable, and changes in the factors that contribute to the formation of the latent variable can impact its level. (Jr. *et al*., 2014).

Evaluation of the Measurement Model (Outer Model)

The first step taken in analysing the research results is evaluating the measurement model to determine the relationship between latent variables and their indicators with the following explanation:

Convergent Validity Indicator Construct

The convergent validity of the measurement model can be seen from the correlation between the indicator and construct scores (loading factor), with the criteria for a loading factor value for each indicator being greater than 0.7, which can be said to be valid. However, a value greater than 0.5–0.6 can already be said to be valid (Latan & Ghozali, 2012).

Table 3: Convergent validity indicator construct

No.	Indicator	Loading Value	Standard Error	P value	Description
1	S1	0.72	0.088	<0.001	*Acceptable of convergent validity*
2	S2	0.797	0.086	<0.001	*Acceptable of convergent validity*
3	S3	0.781	0.086	<0.001	*Acceptable of convergent validity*
4	S4	0.618	0.09	<0.001	*Acceptable of convergent validity*
5	S5	0.593	0.091	<0.001	*Acceptable of convergent validity*
6	S6	0.486	0.094	<0.001	*Acceptable of convergent validity*
No.	**Indicator**	**Loading Value**	**Standard Error**	**P value**	**Description**
1	W1	0.85	0.084	<0.001	*Acceptable of convergent validity*
2	W2	0.773	0.086	<0.001	*Acceptable of convergent validity*
3	W3	0.848	0.084	<0.001	*Acceptable of convergent validity*
4	W4	0.428	0.096	<0.001	*Acceptable of convergent validity*
No.	**Indicator**	**Loading Value**	**Standard Error**	**P value**	**Description**
1	G1	0.746	0.087	<0.001	*Acceptable of convergent validity*
2	G2	0.595	0.091	<0.001	*Acceptable of convergent validity*
3	G3	0.559	0.092	<0.001	*Acceptable of convergent validity*
4	G4	0.72	0.088	<0.001	*Acceptable of convergent validity*
No.	**Indicator**	**Loading Value**	**Standard Error**	**P value**	**Description**
1	B1	0.863	0.084	<0.001	*Acceptable of convergent validity*
2	B2	0.698	0.088	<0.001	*Acceptable of convergent validity*
3	B3	0.866	0.084	<0.001	*Acceptable of convergent validity*
4	B4	0.853	0.084	<0.001	*Acceptable of convergent validity*
5	B5	0.697	0.088	<0.001	*Acceptable of convergent validity*
6	B6	0.734	0.087	<0.001	*Acceptable of convergent validity*

No.	Indicator	Loading Value	Standard Error	P value	Description
1	D1	0.753	0.087	<0.001	*Acceptable of convergent validity*
2	D2	0.528	0.093	<0.001	*Acceptable of convergent validity*
3	D3	0.667	0.089	<0.001	*Acceptable of convergent validity*
4	D4	0.51	0.093	<0.001	*Acceptable of convergent validity*
5	D5	0.765	0.087	<0.001	*Acceptable of convergent validity*
6	D6	0.396	0.097	<0.001	*Acceptable of convergent validity*
7	D7	-0.283	0.1	0.003	*Not Acceptable of convergent validity*
8	D8	0.576	0.092	<0.001	*Acceptable of convergent validity*
No.	**Indicator**	**Loading Value**	**Standard Error**	**P value**	**Description**
1	K1	-0.082	0.106	0.221	*Not Acceptable of convergent validity*
2	K2	0.386	0.097	<0.001	*Acceptable of convergent validity*
3	K3	0.734	0.087	<0.001	*Acceptable of convergent validity*
4	K4	0.33	0.098	<0.001	*Acceptable of convergent validity*
5	K5	0.72	0.088	<0.001	*Acceptable of convergent validity*
6	K6	0.544	0.092	<0.001	*Acceptable of convergent validity*
7	K7	0.578	0.091	<0.001	*Acceptable of convergent validity*
8	K8	0.517	0.093	<0.001	*Acceptable of convergent validity*
9	K9	0.715	0.088	<0.001	*Acceptable of convergent validity*
10	K10	-0.068	0.106	0.263	*Not Acceptable of convergent validity*

Source: Output result of WarpPLS 6.0 processed by the author (2022)

Apart from examining the cross-loadings of the constructs, the convergent validity of a model can also be evaluated using the Average Variance Extracted (AVE) value of the latent variables. A commonly accepted criterion for AVE is that it should be greater than 0.5 to indicate good convergent validity (Solimun *et al.,* 2017). The AVE value of each variable in this study is presented in Table 4. The results of the construct used in this study indicate that the AVE value of all constructs has a value greater than 0.5. Based on these results, it can be concluded that the variables used in this study have met convergent validity.

Discriminant Validity

The criterion of discriminant validity is indicated by more AVE square roots greater than the correlation coefficient between the constructs in each column Discriminant validity can be assessed from the cross-loading value of the construct measurement. If the construct's correlation with each indicator is greater than the construct's size with the other, then the indicator is predicted to be better than the other construct. An presentation of discriminant validity on cross scores loading can be seen in Table 5.

Table 4: The AVE value of variables

No.	Variable	AVE Value	Decription
1	ST	0.675	*Acceptable of convergent validity*
2	WT	0.745	*Acceptable of convergent validity*
3	GT	0.66	*Acceptable of convergent validity*
4	MT	0.581	*Acceptable of convergent validity*
5	BR	0.789	*Acceptable of convergent validity*
6	KT	0.523	*Acceptable of convergent validity*

Source: Output result of WarpPLS 6.0 processed by the author (2022)

Table 5: Discriminant validity on cross scores loading

	ST	WT	GT	MT	BR	KT	SE	P value
S1	-0.65	-0.356	-0.004	0.343	0.271	-0.043	0.1	0.005
S2	-0.695	-0.135	0.356	0.042	0.163	-0.293	0.1	0.002
S3	0.709	-0.173	0.357	-0.123	0.04	-0.121	0.1	0.003
S4	0.7	0.317	-0.353	-0.235	-0.016	0.19	0.101	0.014
S5	0.669	0.434	-0.314	-0.052	-0.337	0.197	0.102	0.018
S6	0.756	0.047	-0.253	-0.065	-0.312	0.242	0.103	0.044
W1	-0.025	0.784	0.191	-0.001	-0.123	0.065	0.097	<0.001
W2	0.299	0.864	-0.257	-0.132	0.282	-0.332	0.098	<0.001
W3	-0.444	0.885	0.293	-0.115	-0.005	0.137	0.097	<0.001
W4	0.489	0.63	-0.514	0.535	-0.332	0.223	0.102	0.032
G1	0.392	-0.172	0.713	0.075	0.159	-0.383	0.096	<0.001
G2	-0.332	0.298	0.706	-0.378	-0.214	0.305	0.098	<0.001
G3	0.098	-0.427	0.734	0.282	-0.037	-0.122	0.099	<0.001
G4	-0.182	0.265	0.657	0.103	0.102	0.227	0.096	<0.001
D1	0.254	-0.186	-0.156	0.95	-0.255	0.097	0.1	0.003
D2	-0.056	0.204	0.048	0.849	-0.179	0.19	0.102	0.03
D3	-0.008	-0.029	0.167	0.91	0.361	-0.514	0.101	0.008
D4	-0.597	0.338	0.332	0.866	0.133	-0.212	0.103	0.035
D5	0.493	-0.182	-0.218	0.873	-0.015	-0.079	0.1	0.003
D6	-0.166	-0.243	0.69	0.479	-0.161	0.32	0.104	0.08
D7	0.074	-0.088	0.796	-0.537	0.149	-0.389	0.105	0.163
D8	-0.538	0.391	-0.081	0.828	0.182	0.294	0.102	0.02
B1	-0.049	-0.051	0.148	0.202	0.738	0.121	0.101	0.013
B2	-0.038	0.311	-0.111	-0.232	0.845	-0.158	0.103	0.036
B3	0.26	-0.131	0.075	-0.005	0.748	-0.147	0.101	0.012
B4	-0.083	-0.103	-0.027	0.119	0.809	0.123	0.101	0.013
B5	-0.027	0.182	-0.234	-0.254	0.869	-0.004	0.103	0.036

B6	-0.139	-0.195	0.144	0.174	0.802	0.103	0.102	0.029
K1	0.158	0.03	-0.483	0.85	-0.12	-0.178	0.108	0.393
K2	-0.152	0.427	-0.394	-0.152	-0.042	0.83	0.104	0.089
K3	-0.032	-0.273	0.233	-0.058	-0.274	0.812	0.1	0.005
K4	-0.395	0.235	-0.197	0.383	0.067	0.703	0.105	0.125
K5	0.17	0.096	-0.267	-0.02	-0.283	0.825	0.1	0.005
K6	-0.202	-0.048	0.544	0.351	0.033	0.646	0.102	0.027
K7	-0.281	-0.305	0.469	0.059	-0.148	0.791	0.102	0.021
K8	0.13	-0.185	-0.389	0.115	0.718	0.672	0.103	0.034
K9	0.246	0.435	-0.198	-0.222	0.484	0.626	0.1	0.005
K10	-0.852	0.289	0.384	-0.167	0.094	-0.175	0.108	0.409

Source: Output result of WarpPLS 6.0 processed by the author (2022)

Based on the data, it can be concluded that only a few constructs meet the criteria of discriminant validity, in which all latent constructs predict their indicators are greater than other indicators.

Composite Reliability and Cronbac's Alpha

Composite reliability testing is a statistical test used to assess the internal consistency and reliability of a set of measures or items within a research instrument Outputs are used to determine the reliability of data, that is the composite reliability and Cronbach's alpha must be both be greater than 0.70 to indicate reliability (Sholihin, 2013). The value of composite reliability and Cronbach's alpha for this study can be seen in Table 6. From these results, it can be concluded that each construct has a high-reliability value. It can be seen that the value of composite reliability is greater than 0.70 and Cronbach's alpha in each construct is greater than 0.50.

Evaluation of the Structural Model (Inner Model)

After testing the evaluation of the measurement model (outer model), where convergent validity, discriminant validity, composite reliability and Cronbach's alpha have met the requirements, the next stage involves the evaluation of the structural model (inner model), which includes the model fit test and R2. The model fit test is used to determine which model used matches the data. In a model fit test, there are 10 test indices (Solimun *et al.,* 2017). Results Output models fit indices in this study can be seen in Table 7. The results of the output model fit indices in this study are presented in Table 7. Based on the results of testing the fit and quality indices model, it can be seen that all criteria have

Table 6: Values of composite reliability and Cronbach's alpha

	ST	WT	GT	MT	BR	KT	Description
Composite reliability coefficients	0.83	0.825	0.752	0.743	0.907	0.725	Acceptable
Cronbach's alpha coefficients	0.753	0.712	0.56	0.62	0.876	0.608	Acceptable

Source: Output result of WarpPLS 6.0 processed by the author (2022)

Table 7: Results of the output models

No.	Model fit and quality indices	Result	Criteria	Description
1	Average Path Coefficient (APC)	0.243		
		P=0.005	P <0.05	Good
2	Average R-square (ARS)	0.177		
		P=0.022	P <0.05	Good
3	Average adjusted R-square (AARS)i	0.158		
		P=0.032	P <0.05	Good
4	Average blok VIF (AVIF)	1.391	acceptable if <= 5, ideally <= 3.3	Ideal
5	Average full collinearity VIF (AFVIF)	1.712	acceptable if <= 5, ideally <= 3.3	Ideal
6	Tenenhaus GoF (GoF)	0.281	small >= 0.1, medium >= 0.25, large >= 0.36	Ideal
7	Sympson's paradox ratio (SPR)	0.889	acceptable if >= 0.7, ideally = 1	Acceptable
8	R-squared contribution ratio (RSCR)	0.999	acceptable if >= 0.9, ideally = 1	Acceptable
9	Statistical suppression ratio (SSR)	1	acceptable if >= 0.7	Acceptable
10	Nonlinear bivariate causality direction ratio (NLBCDR)	0.833	acceptable if >= 0.7	Acceptable

Source: Output result of WarpPLS 6.0 processed by the author (2022)

been met, indicating that the model generated from WarpPLS 6.0 is appropriate for use. The structural model in WarpPLS 6.0 was evaluated using R2 for the mediating variable and the dependent variable, path coefficient value, and p-value to test the significance of the variables in the model.

Results of Influence Analysis between Variables

Overall, this research model is divided into two effects namely direct influence and indirect influence. Great influence can be seen directly in Figure 2 research model; while big indirect effect and total effect can be seen in the WarpPLS Output 6.0 Indirect Total Effect described in Table 8.

Based on the results shown in Figure 2, it can be observed that the P-Value output of the direct effect on the variables of farmer's knowledge of Green Technology (GT), Digital Marketing Technology (MT), Soil Fertiliser Technology (ST), and Water-Saving Technology (WT) indicates a significant value (below alpha 0.05). Additionally, the original sample estimate of the knowledge variables to ST, WT, GT, and MT exhibits a positive value of 0.42, 0.27, 0.29, and 0.18, respectively. The results in Table 8 show the variable BR cannot strengthen the relationship between KT to ST and WT. The variable BR, however, can strengthen the relationship between KT to GT and MT, but changing it does not resolve the direct relationship between KT to GT and MT based on the direct and indirect comparison coefficients on GT (0.29 > 0.115) and on MT (0.18 > 0.099) to be partial mediation variables.

Farmers' knowledge related to agricultural technology influences farmers' decisions to

Table 8: The direct, indirect, and total effects

Variables	Direct Effect (DE)		Indirect Effect (IE)		Total Effect (TE)
	β	p	*β*	p-value	
ST	0.42*	P<0.01	0.07 x 0.55 =0.030	0.25	0.45
WT	0.27*	P<0.01	-0.01 x 0.55=-0.005	0.47	0.27
GT	0.29*	P<0.01	0.21 x 0.55=0.115*	P<0.01	0.40*
MT	0.18*	0.04	0.18 x 0.55=0.099*	P<0.01	0.27*

*significant level 5%

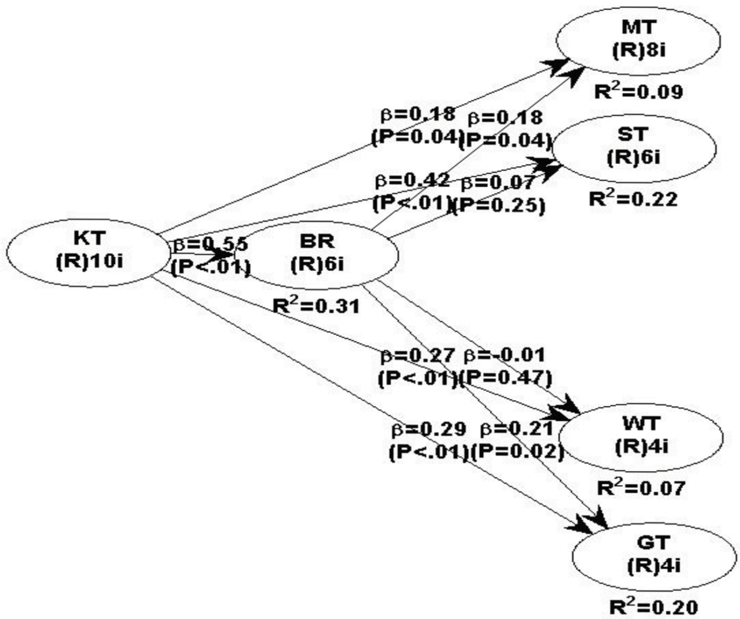

Figure 2: The direct, indirect, and total effects

adopt "soil fertiliser technology" technology. However, if this knowledge is mediated by variables related to farmers' behavior, then it may not have a significant effect. This suggests that the behaviour of farmers, as indicated by variables such as greenhouse usage, organic fertiliser manufacturing, product packaging variation, agricultural product processing, integrated crop management field training, and integrated pest control field training, plays a crucial role in determining the effectiveness of knowledge in promoting the adoption of agricultural technology.In the first set of results, it can be observed that the variable GT has the highest total effect value with a coefficient value of 0.40, followed by MT with a value of 0.27.

On the other hand, the variables ST and WT show no significant total effect. In the second set of results, the variable ST exhibits the highest coefficient value on the direct effect, which is 0.42, followed by WT with a value of 0.27. These findings indicate that, based on farmer knowledge reinforced by their behaviour, farmers are more likely to adopt Green Technology (GT) and Digital Marketing

Technology (MT). However, when considering knowledge alone without mediation by farmer behaviour, farmers tend to adopt Soil Fertiliser Technology (ST) and water-saving technology (WT).

Discussion

Direct Effect of Knowledge on Soil Technology

Based on the analysis of direct influence, it can be concluded that the knowledge variable has a significant positive impact (0.42). This suggests that the knowledge possessed by farmers significantly influences the soil technology adopted. The technology that is widely adopted by farmers in East Java is the new superior varieties and location-specific balanced fertilisation technology. The coefficient value for soil technology adoption is higher than that of other technologies because traditional farming uses soil as a planting medium and the average farmer has over 10 years of farming experience.

According to the social information processing theory, farmers use their experience to comprehensively analyse and evaluate information by gathering relevant environmental information and adjusting their behaviour and decisions accordingly (Braithwaite & Schrodt, 2014). Thus, the experience of farmers in providing balanced fertilisation and soil fertility processing methods makes it easier for them. Hidayati *et al*. (2019) also found that farmers with more farming experience tend to be more efficient than inexperienced farmers. Furthermore, farmers in East Java use tractors, including two-wheeled tractors, which makes it easier for them to adopt soil technology.

Direct Effect of Knowledge on Water Technology

The direct effect analysis results indicate that the knowledge variable has a positive and significant impact on water technology adoption, with a coefficient value of 0.27. This finding is consistent with the research sample data, which shows that 65% of farmers who use traditional irrigation systems do not adopt water-saving irrigation technology. The reasons for this are influenced by social and demographic factors, as Kalirajan (1991) suggests that socio-economic attributes indirectly affect production. Additionally, socio-economic variables have a significant impact on farm size and experience, as noted by Hidayati et al. (2019).

Castillo et al. (2021) found that social capital can trigger the adoption of water-saving irrigation technology by increasing social pressure, strengthening farmers' self-confidence, and influencing farmer associations' core beliefs related to water conservation awareness. Moreover, increasing farmers' trust in water organizations can encourage cooperation, which can lead to the adoption of pressurized irrigation systems as the norm, as suggested by Klockner (2013).

Interestingly, other studies have shown that the cost of water does not affect adoption, as the payment is independent of water consumption. Additionally, farm size has a positive and significant influence on irrigation technology adoption, indicating that larger farmers are more likely to adopt due to economies of scale and greater capacity to bear risks (Diederen et al., 2003).

Direct Effect of Knowledge on Green Technology

The results suggest that the knowledge variable has a significant and positive influence on the adoption of green technology, with a coefficient value of 0.29. This finding indicates that farmers' level of knowledge impacts the adoption of green technology, as evidenced by the 41.76% adoption rate of technologies such as organic fertiliser, waste-free livestock crop integration systems, integrated plant-disturbing organism control, and diversified crops. However, adopting agricultural green production technology can be time-consuming and challenging, and some new generations of farmers may be hesitant to adopt such technology if government incentives or subsidies are insufficient to offset the expected costs and benefits (Pannell *et al*., 2016).

This result contrasts with the findings of Guo (2022), who argued that the new generation of farmers is more open to new ideas than older generations, and that the perception of environmental settings has a greater impact on their adoption of agricultural green production technology. Guo *et al*. (2022) further stated that the impact of social capital, including both embedded and disembedded, has a significant influence on promoting the adoption of agricultural green production technology among both old and new generations of farmers. Nevertheless, compared with older generations of farmers, the new generation may be more influenced by social capital, and it may have a more significant impact on their decision-making regarding green production.

In contrast, older farmers with non-entrenched social capital may expand their social circle, but they are also more vulnerable to the influence of surrounding green production farmers, which can lead to a "herding effect". Therefore, the older generation of farmers' decision-making regarding green production may be more influential than that of the new generation.

Direct Effect of Knowledge on Digital Marketing Technology

The variable "knowledge of digital marketing technology" has the lowest coefficient value (0.18) compared with technology adoption in soil, water, and green technology. The age factor of farmers, particularly those above 45 years old, suggests that less productive farmers may not be familiar with recent digital technology developments such as social media or e-commerce sales. Based on the results of PLS analysis, questions with a significance value below 0.05 include marketing agricultural products through social media, monitoring prices of agricultural products, selling agricultural products through online platforms, funding through online platforms, purchasing agricultural equipment and supplies through mass media or online, and consulting with experts online, as well as using computers or laptops to access information related to agriculture. Questions related to "selling agricultural products to middlemen" have a probability value above 0.05, which is likely due to the fact that the average farmer in East Java sells their products directly to traditional markets, as most agriculture in this area is still on a small scale with an average land area of fewer than 5 hectares. The results of this study are consistent with those of Gao *et al*. (2020), which indicate that the failure of farmers to adopt digital agriculture could lead to unsustainable agriculture. However, differences in agricultural scale (small vs. large farmers) could also affect the adoption of other digital technologies. Nevertheless, according to World Bank data, farmers generally have limited access to technology, knowledge, and financial resources (World Bank, 2017).

Variable Knowledge mediated by farmers' behaviour towards soil technology, water technology, green technology, and digital marketing technology

The first finding suggests that, in the absence of farmer behaviour, the variable ST has the strongest direct effect with a coefficient value of 0.42, followed by WT with a coefficient value of 0.27. These findings support Bandura's (1977) theory of "social learning", which suggests that farmers' attitudes towards technological innovation can be influenced by the natural environment and agro-ecosystems. Farmers who possess knowledge influenced by social learning within their agro system and environmental conditions tend to adopt soil fertilization and water-saving technologies. This is consistent with the findings of Wu *et al*. (2022), which show that the geographical location of households has a significant positive impact on the positive social learning of farmers. Wu *et al*. (2022) also found that social learning can significantly influence farmers' technology learning and adoption behaviour of soil testing technology and formula fertilization technology, indicating that positive social learning increases the possibility of soil testing and formula fertilization technology diffusion.

Based on the insignificant total effect of soil technology and water technology variables, it can be concluded that different farmers have different regulatory environments due to their varying endowments, such as their level of knowledge, social experience, and information-gathering ability. The findings of this study are consistent with those of Gao *et al*. (2020), who demonstrated the risk of unsustainable agriculture when farmers fail to adopt digital agriculture, particularly in the context of differences in agricultural scale. Moreover, rural areas should be viewed as a “relational” society where social capital is an essential complement to the formal system, thus influencing farmers’ perceptions of their environmental settings. However, World Bank data reveals that farmers have limited access to technology, restricted knowledge, and insufficient financial resources (World Bank, 2017). Furthermore, small-scale farmers are often slower to adopt new technologies.

The second finding revealed that based on farmer knowledge, which is reinforced by farmer behaviour, farmers are more likely to adopt technologies related to green technology (GT) and digital marketing technology (MT). According to the total effect, the variable GT has the highest total effect value with a total coefficient value of 0.40. This suggests that farmers who have implemented some or all of the modern agricultural behaviours, as indicated by greenhouses, organic fertiliser production, packaging variations, processing of agricultural products, integrated crop management field training, and integrated pest control field training, are more likely to choose to use green technology (GT) and digital marketing technology (MT). This finding is consistent with the idea that farmers who have already adopted some modern agricultural practices are more open to further technological innovation and are better equipped to integrate new technologies into their operations.

The comparison of research results with social learning theory highlights the addition of exogenous technological dimensions and the expansion of endogenous technologies’ application, where farmers’ attitudes towards technological innovation can be influenced by natural environmental conditions and agroecosystems. These findings are consistent with the research conducted by Wu *et al*. (2022), which demonstrated the significance of positive social learning in the adoption of soil testing and formula fertilization technology. Wu *et al*. (2022) also showed that social learning can significantly influence farmer technology learning and adoption behaviour. It is possible that external reinforcement of soil testing and formula fertilization technology encourages farmer social learning. Furthermore, the geographic location of households was found to have a significant positive impact on social learning and its effects on farmers.

The results of the research expand the validity of the social capital theory pioneered by Bourdieu (2011) and developed by Coleman (1988) and Putnam (1992), namely the concept of social networks, norms, and beliefs. Theoretically, social capital can help farmers gather information, exchange technology and raise funds, effectively compensating for the shortcomings of the formal sector. On the other hand, a comparison between the results of the study and the theory of planned behaviour suggest that social and institutional conditions greatly influence technology adoption. Therefore, it is crucial to consider local knowledge and its application when training farmers on new technologies to increase community participation in mechanisation (Kuntariningsih, 2014). It is important to note that farmers have varying regulatory environments depending on their level of knowledge, social experience, information acquisition ability, among other things (Barnes *et al.*, 2015).

Thus, this research intersects three theories: Social learning theory, social capital theory, and planned behaviour theory to explain farmer preferences in adopting each technology based on their knowledge and behaviour. As a result, the government should concentrate on transferring knowledge and information through social networks to promote action and boost farmers' confidence in meeting technological advancements in agriculture. This will aid in the shift from traditional farming practices to utilising technology to improve efficiency and ultimately enhance the welfare of farmers.

Conclusion

The adoption of agricultural technology is crucial for enhancing the efficiency of farmers, but its implementation has faced challenges. Based on the findings of this research, it can be concluded that farmer knowledge, when reinforced by behaviour, results in a preference for green technology and digital marketing technology. Conversely, when knowledge is not mediated by behaviour, farmers tend to adopt soil fertiliser technology and water-saving technology. To facilitate the adoption of technology, the government can help upgrade farmers' knowledge and encourage modern farming behaviour. However, this study has some limitations, such as its focus on specific areas in East Java province. Therefore, it is recommended to conduct further research in other regions of Indonesia to expand the understanding of the factors affecting technology adoption among farmers.

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References

Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes*, *50*, 179-211.

Alwang, J., Gotor, E., Thiele, G., Hareau, G., Jaleta, M., & Chamberlin, J. (2019). Pathways from research on improved staple crop germplasm to poverty reduction for smallholder farmers. *Agricultural Systems*, *172*, 16-27. https://doi.org/10.1016/j.agsy.2017.10.005

Bandura, A. (1979). *Social learning theory*. Englewood Cliffs, NJ: Prentice Hall.

Barnes, A. P., Willock, J., Hall, C., & Toma, L. (2009). Farmer perspectives and practices regarding water pollution control programmes in Scotland, *Agric. Water Manag*, *96*, 1715-1722. https://doi.org/10.1016/j.agwat.2009.07.002

Bourdieu, P. (2011). *The forms of capital, in the sociology of economic life* (3rd ed.). Routledge.

Bradshaw, C. J. A., & Minin, E. Di. (2019). Socio-economic predictors of environmental performance among African nations. *Scientific Reports*, *9*(9306). https://doi.org/10.1038/s41598-019-45762-3

Braithwaite, D. O., & Schrodt, P. (2014). *Engaging theories in interpersonal communication: Multiple perspectives*. SAGE Publications.

Bukchin, S., & Kerret, D. (2018). Food for hope: The role of personal resources in farmers' adoption of green technology. *Sustainability*, *10*(5), 1615. https://doi.org/10.3390/su10051615

Bukchin, S., & Dorit, K. (2020). Character strengths and sustainable technology adoption by smallholder farmers. *Heliyon*, *6*(8). https://doi.org/10.1016/j.heliyon.2020.e04694

Bunkus, R., Soliev, I., & Theesfeld, I. (2020). The density of resident farmers and rural inhabitants' relationship to agriculture: Operationalizing complex social interactions with a structural equation model. *Agriculture and Human Values*, *37*, 47-63.

Cafer, A. M., & Rikoon, J. S. (2018). Adoption of new technologies by smallholder farmers: The contributions of extension, research institutes, cooperatives, and access to cash for improving tef production in Ethiopia. *Agriculture and Human Values*, *35*(3), 685-699.

Castillo, G. M. L., Engler A., & Wollni, M. (2021). Planned behaviour and social capital: Understanding farmers' behaviour toward pressurized irrigation technologies. *Agric.Water Manag*, *243*(106524). https://doi.org/10.1016/j.agwat.2020.106524

Coleman, J. S. (1988). Social capital in the creation of human capital. *Am. J. Social*, *94.* https://doi.org/10.1086/228943. S95–S120

Diagne, A., & Cabral, F. J. (2017). *Agricultural transformation in Senegal: Impact of an integrated program* (Policy Analysis on Growth and Employment).

Diederen, P., Van Meijl, H., Wolters, A., & Bijak, K. (2003). Innovation adoption in agriculture: Innovators, early adopters and laggards. *Cah. Econ. Social. Rural*, 67, 29-50.

Eweoya, I., Okuboyejo, S. R., Odetunmibi, A. O., & Odusote B, O. (2021). An empirical investigation of acceptance, adoption and the use of E-agriculture in Nigeria. *Heliyon*, *7*(e07588). https://doi.org/10.1016/j.heliyon.2021.e07588

Gao, Y., & Niu, Z. (2019). Risk aversion, information acquisition ability and farmers' adoption behaviour of green control techniques. *Chin. Rural Econ*, *8*, 109-127.

Gao, Y., Zhao, D., Yu, L., & Yang, H. (2020). Influence of a new agricultural technology extension mode on farmers' technology adoption behaviour in China. *Journal of Rural Studies*, *76*, 173-183. https://doi.org/10.1016/j.jrurstud.2020.04.016

Ghozali, I. (2012). *Aplikasi Analisis Multivariate dengan Program IBM SPSS 20 (in Indonesian language)*. Badan Penerbit – Universitas Diponegoro.

Guo, Z., Chen, X., & Zhang, Y. (2002). Impact of environmental regulation perception on farmers' agricultural green production technology adoption: A new perspective of social capital. *Technology in Society, 71*(102085).

Hidayati, B., Yamamoto, N., & Kano, H. (2019). Investigation of production efficiency and socio-economic factors of organic rice in Sumber Ngepoh District, Indonesia. *Journal of Central European Agriculture*, *20*(2),748-758. doi: /10.5513/JCEA01/20.2.2143

Jr., J. F. H., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial Least Squares Structural Equation Modelling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106-121. https://doi.org/10.1108/EBR-10-2013-0128

Kalirajan, K. (1991). The importance of efficient use in the adoption of technology: A micro panel data analysis. *Journal of Productivity Analysis*, *2*(2), 113-126. http://www.jstor.org/ stable/41770542

Klockner, C. A. (2013). A comprehensive model of the psychology of environmental behaviour—Ameta-analysis. *Glob. Environ. Change*, *23*, 1028-1038. https://doi.org/10.1016/j.gloenvcha.2013.05.014

Li, J., Zhang, Y., & Cui, B. (2018). Internet is used to promote the upgrading of agricultural technology extension mode. *Prim. Agriculture Technology Extension*, *6*(1), 7-8.

Loizou, E., Karelakis, C., Galanopoulos, K., & Mattas, K. (2019). The role of agriculture as a development tool for a regional economy. *Agricultural System*, *173*, 482-490. https://doi.org/10.1016/j.agsy.2019. 04.002

Macnaghten, P., Davies, S. R., & Kearnes, M. (2015). Understanding public responses to emerging technologies: A narrative approach. *Journal Environment Policy*, *21*(5), 504-518. https://doi.org/10.1080/1523908X.2015.1053110

Mwangi, M., & Kariuki, S. (2015). Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *Journal Economic Sustainability and Development*, *6*(5).

Nielson, D., Meng, Y.-T., Buyvolova, A., & Hakobyan, A. (2018). *Unleashing the Power of Digital on Farms in Russia – and*

Seeking Opportunities for Small Farms. http://hdl.handle.net/10986/30627

Pannell, D. J., & Claassen R. (2020). The roles of adoption and behaviour change in agricultural policy. *Appl. Econ. Perspect. Pol*, *42,* 31-41. https://doi.org/10.1002/aepp.13009

Pannell, D. J., Marshall, G. R., Barr, N., Curtis, A., Vanclay, F., & Wilkinson, R. (2006). Understanding and promoting the adoption of conservation practices by rural landholders. *Aust. J. Exp. Agric*, *46*, 1407-1424.

Pavlou, P., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. *MIS Quarterly*, *31*(1), 105-136. https://doi.org/10.2307/25148783

Pemerintah Provinsi Jawa Timur. (2021). *Rencana Kerja Pemerintah Daerah (RKPD) Jawa Timur Tahun 2021 (in Indonesian language)*. bappeda.jatimprov.go.id. http://bappeda.jatimprov.go.id/bappeda/wp-ontent/uploads/dokren/rkpd_jatim_2021.pdf

Poppe, K., Wolfert, J., Verdouw, C., & Renwick, A. (2015). A European perspective on the economics of big data. *Farm Policy Journal*, *12*, 11-19.

Putnam R. D. (1992). *Making democracy work: Civic traditions in modern Italy*. Princeton University Press.

Sakar, A., Azim, J. A., Asif, A. A., Qian, L., & Peau, A. (2021). Structural Equation Modeling for indicators of sustainable agriculture: Prospective of a developing country's agriculture. *Land Use Policy*, *109*, 10563.

Sarwono, J., & Narimawati, U. (2015). *Membuat Skripsi, Tesis dan Disertasi dengan Partial Least Square SEM (PLS-SEM) (in Indonesian language)*. ANDI.

Solimun, Adji. A. R. Fernandes, Nurjannah. (2017). *Permodelan Persamaan Stuktural (SEM) Pendekatan* WarpPLS *(In Indonesia language)*. UB Press: Malang.

Sonka, S. (2015). Big data; From hype to the agricultural tool. *Farm Policy Journal*, *12*, 1-9.

The Economist Impact. (2021). *Global Food Security Index*. impact.economist.com. https://impact.economist.com/sustainability/project/food-security-index/Country/Details#Indonesia

Theis, S., Lefore, N., Meinzen-Dick, R., & Bryan, E. (2018). What happens after technology adoption? Gendered aspects of small-scale irrigation technologies in Ethiopia, Ghana, and Tanzania. *Agriculture Human*, *35*, 671-684.

Theocharopoulos, A., Aggelopoulos, S., Papanagiotou, P., Melfou, K., & Papanagiotou, E. (2012). Sustainable Farming Systems vs Conventional Agriculture: A socioeconomic approach, sustainable development - Education, business and management - Architecture and building construction. In *Agriculture and Food Security*. https://doi.org/10.5772/27537

World Bank. (2017). *ICT in Agriculture (Updated Edition): Connecting smallholders to knowledge, networks, and institutions*.

Wu, Haixia., Li, Jianping., & Ge Yan. (2022). Ambiguity preference, social learning and adoption of soil testing and formula fertilization technology. *Technological Forecasting & Social Change*, *184*(122037). https://doi.org/10.1016/j.techfore.2022.122037

Yin, R., Luo, X., Li, R., & Huang, Y. (2018). Under the background of informatization, why do farmers favour agricultural technicians to carry out agricultural technology extension in the field? *Res. Agriculture Modern*, *39*(4), 576-583.