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Towards Economic Resilience and Food Security: Leveraging Livelihood Capital and Technology for Farmer Adaptation in East Java, Indonesia

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Abstract

The agricultural sector's contribution in East Java Province diminished**,** primarily due to the prevalence of traditional farming practices, reliance on climate variability, and limited adoption of modern technology. These challenges resulted in seasonal poverty and heightened vulnerability for many farmers, impacting their economic resilience and food security. This study examined the impact of various livelihood assets on farmers' adaptive capacities in East Java, utilizing Structural Equation Modelling-Partial Least Squares (SEM-PLS) to explore both direct and indirect relationships between livelihood capital and adaptation levels. The findings revealed that livelihood capital significantly enhanced farmers' adaptive capacities directly and indirectly. Moreover, strong livelihood capital contributed positively to farmers' resilience to climate change, thus promoting food security in the region. These results underscore the crucial role of bolstering livelihood capital as an effective strategy to enhance farmers' adaptive capacity and address vulnerability challenges, ultimately supporting food security.

Keywords: Economic resilience, Food Security, Livelihood Capital, Technology
JEL Classification: O1, Q1, R1

INTRODUCTION

Agriculture is a pillar of Indonesia's economy that supports the sustainability of national food security. However, this sector faces challenges such as climate variability, limited access to appropriate technology, and economic fluctuations (Susanti et al., 2019). These constraints pose critical issues for the livelihoods of small-scale farmers who rely heavily on natural resources to maintain productivity and food security (Putri et al., 2021). One way to sustain productivity, stabilize household income, and improve access to real-time information is by integrating technology into agriculture (Bayih et al., 2022; Morepje et al., 2024; Paul et al., 2022). Technologies such as precision farming, data-driven crop management, and digital marketplaces can assist farmers in overcoming traditional barriers by providing real-time data and continuous market information (Balyan et al., 2024; Mgendi, 2024).

Although some studies have examined the relationship between livelihood capital and food security or climate change adaptation, most of these studies have not considered the role of technology comprehensively. In fact, the adoption of agricultural technology has been shown to increase farmer productivity and resilience (Kurdi et al., 2023; Triman Tapi et al., 2024). However, factors influencing the level of technology adoption in relation to livelihood capital in East Java have not been thoroughly and comprehensively studied. This study aims to analyze the influence of livelihood assets on farmer adaptation in East Java, considering technology integration as a critical factor. A deeper understanding of the interaction between livelihood capital, technology, and farmers' adaptive capacity is expected to ensure economic resilience and interventions in improving food security at the regional and national levels. Therefore, this research is not only important for strengthening the agricultural sector but also crucial in supporting economic stability and sustainable food security in the future.

Farmers' adaptation to environmental and socio-economic changes is critical to maintaining agricultural productivity. The concept of livelihood assets, which includes human, natural, financial, physical, and social capital, has been identified as an essential factor influencing farmers' adaptive capacity (Chepkoech et al., 2020; Datta & Behera, 2022). However, the integration between livelihood capital and technology adoption in the context of adaptation, especially in the agricultural sector in East Java, has not been comprehensively explored. Several recent studies have shown the importance of livelihood capital in improving food security and farmer adaptation. Research on livelihood adaptation has been studied in various quantitative and qualitative contexts, reviewing the factors influencing risk and adaptation behavior (Budhathoki et al., 2020), the socio-ecological system (Afkhami et al., 2022), psychology (Abunyewah et al., 2024), and the application of technology (Mukisa et al., 2020).

East Java Province has a strategic role in maintaining food security, but it also faces complex problems. The latest data shows that rice production in 2023 will reach 9.7 million tons, down 4.8% from 2018's 10.2 million tons (BPS, 2024). This decline is caused by various factors such as climate change and socio-economic policies, which will undoubtedly increase the vulnerability of farmers' livelihoods (Arifah et al., 2022; T. D. N. Ho et al., 2021; Roxburgh et al., 2021).

Climate change poses a severe threat to agricultural productivity in East Java. The Meteorology, Climatology, and Geophysics Agency (BMKG) recorded increased frequency and intensity of extreme climate events in the region. In 2022, there were climatological disasters, namely 153 floods and 157 extreme weather events in East Java (BPS, 2023). This phenomenon directly impacts cropping patterns, water availability, and the risk of crop failure. In addition, socio-economic challenges also complicate efforts to increase food security. There was an increase in small farmers, namely 10.61% from 2013, from 4.9 million to 5.5 million (BPS Provinsi Jawa Timur, 2023). This phenomenon directly impacts cropping patterns, water availability, and the risk of crop failure. In addition, socio-economic challenges also complicate efforts to increase food security. There was an increase in small farmers, namely 10.61% from 2013, from 4.9 million to 5.5 million (Suud et al., 2023).

Despite its vital role in supporting Indonesia's food security, the agricultural sector in East Java faces a confluence of complex, interrelated challenges. First, the increasing variability of climate patterns has introduced significant uncertainty in agricultural production. As climate change accelerates, East Java has experienced more frequent extreme events such as floods, droughts, and erratic rainfall, directly threatening water availability, cropping calendars, and yield stability (BMKG, 2023; Arifah et al., 2022; Roxburgh et al., 2021). These environmental stresses have made traditional farming practices increasingly unsustainable, leaving farmers vulnerable to crop failure and income loss (Putri et al., 2021).

Second, socio-economic constraints amplify these vulnerabilities. The notable rise in the number of smallholder farmers, coupled with stagnant or even declining rice production, highlights a structural problem: a growing population dependent on shrinking productive resources (BPS Jawa Timur, 2023; Suud et al., 2023). Rice production in 2023 fell by 4.8% compared to 2018, signaling a downward trend that threatens regional food security (BPS, 2024). This intensifies pressure on already limited livelihood assets, including access to credit, market information, and productive land, all of which are critical for sustaining farm household resilience (Chepkoech et al., 2020; Datta & Behera, 2022). As more farmers struggle to maintain profitability, their capacity to invest in climate-adaptive or productivity-enhancing measures diminishes, creating a vicious cycle of vulnerability (Kurdi et al., 2023).

Third, although technology offers a potential lifeline through precision farming, digital market access, and data-driven decision support, its adoption remains uneven (Bayih et al., 2022; Morepje et al., 2024; Balyan et al., 2024; Mgendi, 2024). This is partly due to structural inequalities in farmers' livelihood assets. For example, farmers with limited human capital (e.g., education, skills), weak social networks, or low financial capital are less able to access and adopt new technologies (Paul et al., 2022; Mukisa et al., 2020). While previous studies have examined the effects of technology adoption or the importance of livelihood assets, few have integrated these two dimensions to understand how different forms of livelihood capital either enable or constrain technology adoption for climate adaptation and productivity improvement (Triman Tapi et al., 2024). This is a critical research gap that must be addressed to strengthen agricultural resilience in East Java.

Moreover, the literature often treats technology adoption as an isolated variable, overlooking how it interacts with the multiple capitals that shape farmers' decisions. Livelihood assets including human (knowledge, skills), social (networks, organizations), natural (land, water), financial (savings, credit), and physical (infrastructure) capitals are not only individually significant but also interact dynamically to influence farmers' adaptive strategies (Chepkoech et al., 2020; Datta & Behera, 2022). Understanding these interactions is essential to designing policy interventions that are both effective and equitable (Budhathoki et al., 2020; Afkhami et al., 2022; Abunyewah et al., 2024).

In the East Java context, where food security is vital to regional and national stability, failing to address these interconnected problems could result in long-term systemic risks. Climate change impacts, combined with socio-economic pressures and technological divides, threaten not only agricultural output but also broader goals of economic stability, poverty reduction, and sustainable development (Susanti et al., 2019; Arifah et al., 2022).

Therefore, the research problem centers on how the interplay of livelihood capital influences technology adoption and adaptive capacity among smallholder farmers in East Java. Exploring this intersection comprehensively will allow researchers and policymakers to identify leverage points for interventions that enhance farmers' resilience while sustaining agricultural productivity. Without such an integrated understanding, interventions risk being fragmented, inequitable, or ineffective in supporting long-term food security (Kurdi et al., 2023; Triman Tapi et al., 2024).

The novelty of this research lies in its ability to bridge the theoretical and practical gaps by examining the collective integration of livelihood capital and technology. The previous studies that focus on isolated aspects of either livelihood capital or technology, this study introduces a multi-dimensional framework that evaluates their synergistic effects on adaptive capacity. This research emphasizes how technology can amplify the benefits of each type of livelihood capital and investigates the resulting impact on both economic resilience and food security.

LITERATURE REVIEW

The literature on agricultural resilience and food security highlights numerous challenges faced by farmers, particularly regarding climate variability, economic fluctuations, and limited access to modern technologies. Previous studies have often examined the roles of livelihood capital and technology independently, with limited exploration of their synergistic potential in enhancing adaptive capacity and economic resilience. This research aims to address this gap by investigating how the integrated use of livelihood capital and technology can improve farmers' resilience and support sustainable food security.

Evolution of the Food Security Concept in the Context of Global Change

The concept of food security has undergone significant evolution over the past few decades. The initial focus of food security studies was only on availability, but now it has been expanded to include dimensions of Physical, social, and economic (Food and Agriculture Organization, 2021). The development of these dimensions reflects a deeper understanding of the increasingly complex global food system. Although comprehensive (Misselhorn, 2005), the framework of food resilience of social-political, education, and technology analysis in understanding food security. In Indonesia, especially East Java (Amelia & Munim, 2023), a resilient food system approach has been applied in their longitudinal study. This study showed that interventions that connect components of the food system are more effective in improving food security compared to sectoral approaches.

Adaptive Capacity

Increasing farmers' adaptive capacity is an urgent issue that must be addressed immediately. The Department for International Development (DFID) has issued a sustainable livelihood strategy through livelihood assets consisting of human, social, natural, financial, and physical capital to improve farmers' abilities and opportunities in dealing with vulnerabilities. Livelihood Assets can increase income, farmers' livelihood adaptive capacity, and livelihood resilience (Bathaiy et al., 2021; Guo et al., 2022; Ma et al., 2024; Vinti & Vaccari, 2022). Livelihood assets play a very important role in improving farmers' adaptability. This is reinforced by a study on strengthening existing livelihood assets that can effectively reduce intergenerational poverty, encourage sustainable growth, and social progress of farmers (Ma et al., 2024).

Integrating Livelihood Capital and Technology: A New Paradigm in Food Security

Integrating livelihood capital with technology adoption has offered a new perspective on enhancing food security. The integration enables a more holistic understanding of farmers' adaptation strategies(Bruno et al., 2021). However, Klerkx et al. (2023) caution against potential unintended consequences of technology adoption, such as the marginalization of small-scale farmers. These findings align with the study by Amelia & Munim (2023), who evaluated the impact of agricultural digitalization programs in East Java. Although these programs increased incomes, there was a digitalization gap caused by differences in farmers' education. Thus, it is essential to consider heterogeneity within farming communities when designing technology interventions. If information technology can be utilized effectively and efficiently, it could be a powerful asset for enhancing farmers' adaptability. (Bruno et al., 2021; Pronti et al., 2024) suggest that information technology significantly influences farmers' adaptive capacity. This study indicates that access to information technology is a driver for adopting environmentally sustainable technologies, such as advanced irrigation systems and improved marketing methods. However, neither study integrates observations into a comprehensive model that considers how various livelihood capitals interact to strengthen farmers' overall adaptive capacity.

Furthermore, Rose et al. (2021) examine the role of sensors and IoT in providing real-time data on microclimate variability, thereby increasing farmers' awareness and enabling more informed decision-making. Although Rose et al.'s research offers insights into microclimate monitoring, it lacks depth regarding how increased awareness of climate variability translates into overall adaptive capacity and economic resilience on a larger scale. Enhanced adaptive capacity can significantly improve the economic resilience of small-scale farmers, which is a crucial factor in reducing vulnerability to external shocks such as climate change, market volatility, and socio-economic pressures. These findings align with (Stringer et al., 2020) those of those who found that farmers with higher adaptive levels are better able to maintain consistent food production even under adverse conditions. Both studies highlight the importance of policies supporting education and innovation to enhance adaptability.

However, neither fully considers the role of technology integration in amplifying these effects within the broader context of livelihood capital. Collectively, these studies underscore the importance of digital technology in improving farmers' adaptive capacity and economic resilience. As discussed by Klerkx et al. (2019) and Rose et al. (2021), access to real-time market information equips farmers to respond to market fluctuations and environmental changes proactively. Similarly, Fielke et al. (2020) show how digital technology facilitates farmers' engagement with technological practices and fosters farmer-led innovation."

METHOD

The method used to provide a thorough understanding of the relationships between livelihood capital, technology adoption, and farmers' adaptive capacity requires a detailed research methodology. This section outlines the research design, data collection methods, and analytical techniques employed to ensure robust and reliable findings. The selected approach is tailored to address the complexity of interactions within the study variables and the context-specific factors influencing farmers' resilience and food security.

Research Design

This study uses a cross-sectional design with a multivariate-based quantitative approach to primary data. This approach was chosen because it can analyze complex models with a relatively small sample size and does not require normally distributed data (Hair et al., 2019). This design allows for the simultaneous analysis of relationships between multiple latent and observed constructs and testing for mediation and moderation effects (Sarstedt et al., 2020).

Population and Study

This study was conducted in East Java Province, focusing on six districts: Mojokerto City, Banyuwangi, Bondowoso, Batu, Malang, and Blitar Regency. The selection of these study areas was purposive and based on several strategic considerations. First, these districts are major agricultural production centers in East Java, contributing significantly to regional and national food security targets (BPS Jawa Timur, 2024). Their agricultural activities include rice, horticulture, and plantation commodities, making them crucial to the province's agricultural sustainability. Second, the districts collectively represent a diversity of agroecological conditions, from lowland paddy fields in Banyuwangi and Bondowoso to highland horticultural systems in Batu and Malang, as well as mixed-crop areas in Mojokerto and Blitar. This diversity is vital to capture the heterogeneity of adaptation strategies and technology adoption across different farming systems.

Third, these districts have been identified as vulnerable to climate-related risks, including increased frequency of droughts, floods, and extreme weather events (BMKG, 2023). Understanding how farmers in these vulnerable areas adapt to these challenges will provide important insights for strengthening resilience. Fourth, the districts display a range of socio-economic characteristics, including differences in farmer demographics, landholding sizes, income levels, and market access. This variation is expected to enrich the analysis of livelihood assets and technology adoption, making the findings more generalizable to the wider East Java farming community. Lastly, these districts are priority areas for government agricultural development and climate adaptation programs, ensuring that the research findings will be relevant and applicable to policy interventions and regional planning efforts.

The population in this study was farmers in East Java Province from six districts, namely Mojokerto City, Banyuwangi, Bondowoso, Batu, Malang, and

Blitar Regency. The number of samples used in this study is calculated using the Slovin formula:

$$n = \frac{N}{1 + N.e^2}$$

$$n = \frac{107}{1 + 107.0.05^2}$$

$$n = 84{,}5$$

Description:
N = total population
n = sample size
e = error

Research Instrument

The data collection instrument used was a questionnaire. This questionnaire was compiled based on a comprehensive literature review and has been adjusted to the empirical conditions of the research location. The variables and indicators of this study are explained in Table 1.

Table 1. Variable and Indicator

No.	Variables	Indicator
Exogen Variable		
1	Information Technology (IT)	$IT_{1.1}$ Trend
		$IT_{1.2}$ Innovation
		$IT_{1.3}$ Training
Manifest Variables		
2	Vulnerability (K)	$K_{2.1}$ Quality of Results
		$K_{2.2}$ Productivity of Results
		$K_{2.3}$ Cost Efficiency
		$K_{2.4}$ Sales
3	Sensitivity (S)	$S_{3.1}$ Market Price
		$S_{3.2}$ Access to Information
		$S_{3.3}$ Policy
4	Adaptation (A)	$A_{4.1}$ Greenhouse construction
		$A_{4.2}$ Product processing
		$A_{4.3}$ Integrated Crop Processing Field School
		$A_{4.4}$ Integrated Pest Control Field School
Endogen Variables		
5	Environmental Technology (TL)	$TL_{5.1}$ Use of new superior varieties
		$TL_{5.2}$ Fertilization technology
		$TL_{5.3}$ Autonomous technology
		$TL_{5.4}$ Crop diversification
		$TL_{5.5}$ Crop diversification
6	Irrigation Technology (TI)	$TI_{6.1}$ Drip irrigation
		$TI_{6.2}$ Water harvesting
		$TI_{6.3}$ Pipeline Irrigation Network Technology
7	Marketing Technology (TP)	$TP_{7.1}$ Marketing through social media
		$TP_{7.2}$ Product price monitoring
		$TP_{7.3}$ Sales through digital platforms
		$TP_{7.4}$ Purchasing agricultural needs online

All variables are measured using a 5-point Likert scale: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree. This research instrument has been tested for reliability and validity. Where reliability is carried out using Warp-PLS software with a Cronbach's alpha value> 0.70, this research instrument can be said to have met composite reliability. Moreover, validity is carried out using the results of the loading value> 0.30 (Solimun et al., 2017). The descriptive statistics about the variables in Table 2.

Table 2. Descriptive Statistics

Variables	Code	Detailed Indicator Description	Min	Max	Median	Mean	Std. Dev.
Information Technology (IT)	IT1.1	The extent to which farmers follow current IT trends	1	5	4	3.64	1.17
	IT1.2	Farmers' perception of innovation in IT for farming	1	5	3	3.42	0.96
	IT1.3	Participation in IT-related training for agricultural practices	1	5	4	3.96	1.18
Vulnerability (K)	K2.1	Perceived quality of agricultural outputs under environmental and market risks	1	5	3	3.24	1.19
	K2.2	Perceived productivity levels under climate and market stress	1	5	3	3.14	1.01
	K2.3	Farmers' ability to keep production costs efficient under stress conditions	1	5	3	3.05	0.97
	K2.4	The ability to maintain sales levels in volatile conditions	1	5	4	3.39	1.21
Sensitivity (S)	S3.1	How vulnerable farmers feel to changing market prices	1	5	3	2.71	1.12
	S3.2	How easily farmers can access reliable agricultural information	1	5	3	2.88	1.11
	S3.3	Perceptions of the impact of agricultural policy changes on their livelihood	1	5	3	2.76	1.23
Adaptation (A)	A4.1	Practices of greenhouse construction to adapt to climate conditions	1	5	2	2.09	1.11
	A4.2	Practices in processing products to add value	1	5	2	2.35	1.15
	A4.3	Participation in integrated crop processing field schools	1	5	2	2.08	1.22

	A4.4	Participation in integrated pest management field schools	1	5	1	2.05	1.22
Environmental Technology (TL)	TL5.1	Adoption of new superior crop varieties	1	5	4	3.08	1.68
	TL5.2	Use of modern fertilization technologies	1	5	4	3.26	1.52
	TL5.3	Adoption of autonomous farming technology	1	5	2	2.44	1.30
	TL5.4	Crop diversification practices	1	5	3	2.69	1.57
Irrigation Technology (TI)	TI6.1	Adoption of drip irrigation systems for water efficiency	1	5	1	1.58	1.17
	TI6.2	Use of water harvesting techniques	1	5	2	2.55	1.58
	TI6.3	Development of pipeline irrigation networks for more reliable water delivery	1	5	1	1.99	1.51
Marketing Technology (TP)	TP7.1	Use of social media platforms for marketing products	1	5	1	2.19	1.47
	TP7.2	Use of digital tools for product price monitoring	1	5	2	2.31	1.36
	TP7.3	Sales activities through digital platforms	1	5	1	1.58	1.02
	TP7.4	Online purchasing of agricultural needs	1	4	1	1.69	0.86

SEM analysis has been widely used to analyze the effect of livelihood capital on adaptation levels (Budhathoki et al., 2020). This method was selected based on the complexity of the model and the relatively small sample size of the study (Hair et al., 2019). In this study, data were analyzed using the Warp-PLS version 7.0 application.

RESULTS AND DISCUSSION

Evaluation of measurement model (outer model)

Outer model measurement is conducted to test the research instrument. In this SEM analysis, convergent validity and discriminant validity are considered.

Convergent validity indicator of the construct

The convergent validity construct can show the correlation between the reflective indicator score and the scores of other variables. The convergent validity value can be seen from the factor loading value, where if the factor loading is >0.30 and $p<0.001$, then it can be said to meet convergent validity (Solimun et al., 2017). A construct can be considered convergent valid if it has an AVE value >0.5 (Solimun et al., 2017).

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Table 3. Result of Convergent Validity

No	Indicator	Loading Factor	AVE	Description
1	IT1.1	(0.764)		
2	IT1.2	(0.688)	0.576	
3	IT1.3	(0.819)		
4	K2.1	(0.887)		
5	K2.2	(0.902)	0.708	
6	K2.3	(0.800)		
7	K2.4	(0.767)		
8	S3.1	(0.835)		
9	S3.2	(0.803)	0.668	
10	S3.3	(0.814)		
11	A4.1	(0.706)		
12	A4.2	(0.700)	0.590	Accepted Convergent Validity
13	A4.3	(0.794)		
15	A4.4	(0.860)		
16	TL5.1	(0.760)		
17	TL5.2	(0.783)	0.533	
18	TL5.3	(0.673)		
19	TL5.4	(0.701)		
20	TI6.1	(0.852)		
21	TI6.2	(0.794)	0.704	
22	TI6.3	(0.869)		
23	TP7.1	(0.758)		
24	TP7.2	(0.714)	0.550	
25	TP7.3	(0.673)		
26	TP7.4	(0.816)		

Source: Output result of WarpPLS 7.0 processed by author (2024)

Based on the results of the discrimination validity test, as shown in Table 3, all indicators in this study have fulfilled discrimination validity, namely, the AVE value> 0.05 and loading factor> 0.30.

Discrimination Validity

In addition to convergent testing, discriminant testing of research instruments is also carried out. Discriminant validity measures the extent to which a construct is genuinely different from other constructs. Discriminant validity testing can use two approaches, namely cross-loading and heterotrait-monotrait ratio (HTMT). Where the loading value must be greater than the cross-loading, discriminant validity can be fulfilled. Meanwhile, the construct fulfils discriminant validity if the HTMT value is <0.90 (Sholihin & Ratmono, 2021). After testing, the results show that all constructs have fulfilled discriminant validity with an HTMT value <0.90.

Table 4. The HTMT value of the Variable

	IT	K	S	A	TL	TI	TP
IT							
K	0.46						
S	0.61	0.201					
A	0.458	0.175	0.22				
TL	0.705	0.385	0.694	0.579			
TI	0.344	0.132	0.342	0.41	0.418		
TP	0.749	0.142	0.523	0.578	0.406	0.21	

Source: Output result of HTMT Rat WarpPLS 7.0 processed by author (2024)

Table 5. Discriminant Validity Among Latent Variables

	IT	K	S	A	TL	TI	TP
IT	(0.759)	0.340	-0.418	0.318	0.469	0.245	0.507
K	0.340	(0.841)	-0.155	0.066	0.305	0.049	0.055
S	-0.418	-0.155	(0.817)	-0.168	-0.509	-0.262	-0.391
A	0.318	0.066	-0.168	(0.768)	0.426	0.309	0.439
TL	0.469	0.305	-0.509	0.426	(0.730)	0.282	0.205
TI	0.245	0.049	-0.262	0.309	0.282	(0.839)	0.158
TP	0.507	0.055	-0.391	0.439	0.205	0.158	(0.742)

Note: The values on the diagonal (highlighted in yellow) represent the square roots of the Average Variance Extracted (AVE) for each construct. Discriminant validity is established when the square root of the AVE for each construct is greater than its correlation with any other construct in the model.

Based on the test results, all constructs met discriminant validity, namely, the loading value was more significant than the other cross-loading values. For example, the IT variable with a loading of 0.579 and cross-loading of 0.340, -0.418, 0.318, 0.469, 0.245, and 0.507 meets discriminant validity.

Composite reliability and Cronbach's Alpha

The validity of the research instrument was also tested for instrument reliability. The reliability test in Warp-PLS consists of two tests: the composite reliability test and Cronbach's alpha. This test is carried out to determine the consistency of the instrument that has been prepared and how far the research instrument can capture empirical conditions in the field. A variable can be said to have composite reliability if it has a value of ≥0.70 and can be said to meet the Cronbach alpha if it has an alpha value of >0.6 (Hair et al., 2011, 2023).

Table 6. Result of Composite Reliability and Cronbach's Alpha

Variable	Composite Reliability Coefficient	Cronbach's Alpha
IT1.1	0.802	0.629
K2.1	0.906	0.860
S3.1	0.858	0.751
A4.1	0.851	0.765
TL5.1	0.820	0.707
TI6.1	0.877	0.789
TP7.1	0.830	0.726

Source: Output result of WarpPLS 7.0 processed by author (2024)

Based on the reliability test results, all research variables met the composite reliability and Cronbach's alpha. The highest alpha reliability was K (Vulnerability), and the lowest was IT (Information Technology). However, these values are still quite acceptable.

Model fit and Quality Indices.

The goodness-of-fit model (Gof) measures the index and size of goodness in the relationship between latent variables and their assumptions. The model fit section presents several fit indicator results, such as APC, ARS, and AVIF. The p-value is given to the APC and ARS indicators based on resampling estimates and Bonferroni-like correlation, because these two fit indicators show the average parameters. Where the p-value of APC and ARS must be <0.05 (Solimun et al., 2017).

Table 7. Result Output Model Fit and Quality

No.	Model Fit and Quality Indices	Fit Criteria	Analysis Result
1.	Average path coefficient (APC)	P< 0.05	0.298 (P<0.001)
2.	Average R-squared (ARS)	P< 0.05	0.223 (P=0.008)
3.	Average adjusted R-squared (AARS)	P< 0.05	0.206 (P=0.012)
4.	Average block VIF (AVIF)	acceptable if <= 5, ideally <= 3.3	1.059
5.	Average full collinearity VIF (AFVIF)	acceptable if <= 5, ideally <= 3.3	1.606
6.	Tenenhaus GoF (GoF)=0.372	small >= 0.1, medium >= 0.25, large >= 0.36	0.372
7.	Sympson's paradox ratio (SPR)	acceptable if >= 0.7, ideally = 1	0.833
8.	R-squared contribution ratio (RSCR)	acceptable if >= 0.9, ideally = 1	0.971
9.	Statistical suppression ratio (SSR)	acceptable if >= 0.7	1.000
10.	Nonlinear bivariate causality direction ratio (NLBCDR)	acceptable if >= 0.7	1.000

Source: Output result of WarpPLS 7.0 processed by author (2024)

Based on the test results of the fit and quality indices model, it was found that all criteria have been met and are suitable for use. The APC value is one important indicator that can be seen when comparing the best models. The APC value will be lower if there is a difference in the sign (positive or negative) of the path coefficient, which is often referred to as the suppression phenomenon.

Result of Relationship Analysis between variables

The magnitude of this relationship can be seen in Figure 1 of the research model, while the direct relationship model is in Table 8, and the indirect relationship is in Table 9. Based on the analysis results explained in Figure 1, it can be observed that almost all output p-values that affect the application of agricultural technology have a significant effect with a p-value <0.05.

Variables that do not have a considerable impact are the effects on TL and K. In addition, the estimated variable of technological information on K and A shows positive values of 0.344 and 0.327, respectively, but has a negative value on the S variable of -0.428. The estimation of the Vulnerability (K) variable to TI and TP shows negative values of -0.064 and -0.133, respectively, but has a positive value on the TL variable of 0.189. This indicates that the higher the vulnerability of fishermen, the smaller their application of environmental technology, irrigation technology, and marketing technology will be.

All estimates of the Sensitivity (S) variable to TL, TI, and TP have negative values of -0.447, -0.232, and -0.311, respectively. This indicates that the higher the sensitivity value owned by farmers, the lower the level of technology adoption they have. Moreover, the adaptation variable (A) to TL, TI, and TP has positive values, namely 0.362, 0.334, and 0.404. This indicates that the higher the farmer's adaptation, the higher the level of agricultural technology adoption will be.

Table 8. Result of Direct Relationship

No.	**Relationship of Variable**		**Path Coefficient**	**P-value**
1.	IT	K	0.344	<0.001
2.	IT	S	-0.428	<0.001
3.	IT	A	0.327	<0.001
4.	K	TL	0.189	0.035
5.	K	TI	-0.064	0.274
6.	K	TP	-0.133	0.104
7.	S	TL	-0.447	<0.001
8.	S	TI	-0.232	0.012
9.	S	TP	-0.311	0.001
10.	A	TL	0.362	<0.001
11.	A	TI	0.334	<0.001
12.	A	TP	0.404	<0.001

Source: Output result of WarpPLS 7.0 processed by author (2024)

Based on the analysis results in Table 8, the p-value for all variables has a value of <0.0001, which indicates a very high level of significance. In contrast, the IT to TI variable mediated by K has a significant significance level of <0.05. The indirect relationship of the information technology variable with the mediation of the vulnerability variable (K) to TL, TI, and TP has a favorable path coefficient value of 0.375, 0.186, and 0.222, respectively.

The vulnerability variable (K) is a partial mediation variable. At the same time, the indirect relationship of TL mediated by sensitivity (S) to TL, TI, and TP has a positive value of 0.191, 0.099, and 0.133, respectively, with a very significant p-value, so it can be said that the variable S is a partial mediation variable. The indirect relationship between IT mediated by the adaptation variable (A) on TL, TI, and TP has a positive value of 0.118, 0.109, and 0.132, respectively, with a highly significant p-value, so it can be said that the variable S is a partial mediation variable.

Table 9. Result of Indirect Relationship

Relationship Between Variables			Path Coefficient (β)	p-value
IT	K	TL	0.375	<0.001
IT	K	TI	0.186	0.037
IT	K	TP	0.220	0.017
IT	S	TL	0.191	<0.001
IT	S	TI	0.099	0.012
IT	S	TP	0.133	0.001
IT	A	TL	0.118	<0.001
IT	A	TI	0.109	<0.001
IT	A	TP	0.132	<0.001

Source: Output result of WarpPLS 7.0 processed by author (2024)

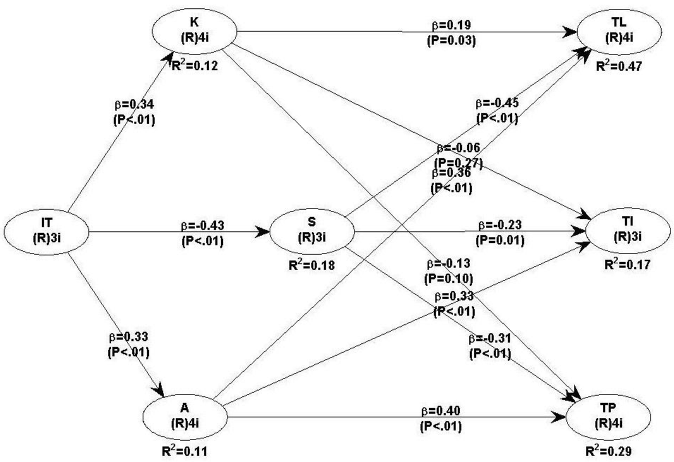

Figure 1. Result Model of Direct, Indirect, and Total Effect
Source: Output result of WarpPLS 7.0 processed by author (2024)

Direct Relationship

Technology Information (IT) has a highly significant positive relationship with Vulnerability (K) and Adaptation Level (A), but a negative relationship with Sensitivity (S). Information technology can increase farmers' awareness of their vulnerability to climate change and other agricultural risks (K. L. P. Ho et al., 2022). Information technology can also improve their adaptive capacity by providing access to better agricultural information and practices (Antwi-Agyei & Stringer, 2021). However, the negative relationship with sensitivity may indicate that increased IT use makes farmers less sensitive to immediate environmental changes, which is a concern. (K) has a significant positive effect on Environmental Technology (TL) but not significantly on Irrigation Technology (TI) and Marketing Technology (TP).

Awareness of vulnerability drives the adoption of better environmental technologies, such as soil and water conservation practices (Aryal et al., 2020; Wang et al., 2021). However, the lack of significant effects on IT and TP suggests that awareness of vulnerability alone may not be enough to drive investment in more advanced irrigation or marketing technologies. Variable S significantly negatively affects TL, TI, and TP. This indicates that farmers who are more sensitive to environmental changes tend to be more conservative in adopting new technologies (Khoza et al., 2021). They may prefer traditional methods that have proven successful in the long term. Effect of Adaptation Level (A): A significantly positive effect on TL, TI, and TP. Farmers with higher levels of adaptation are more likely to adopt various technologies to improve their productivity and sustainability (Khoza et al., 2021; Stringer et al., 2020). This includes environmental technologies for better resource management, irrigation technologies for water use efficiency, and marketing technologies for better market access (Serote et al., 2021).

Indirect Relationship Variable

The results of the analysis show that IT has a significant influence on farmers' vulnerability (K), sensitivity (S), and level of adaptation (A), which has an impact on the application of environmental technology (TL), irrigation (TI), and marketing (TP). The influence of IT on the mediation of farmer vulnerability is proven to be very significant, especially regarding the application of environmental technology ($\beta = 0.375$, $p < 0.001$).

Increased access to technological information allows farmers to better understand their vulnerability to climate change and other agricultural risks. These results are supported by research (Saiz-Rubio & Rovira-Más, 2020), which explains that access to real-time data can help farmers identify vulnerabilities and the level of appropriate technology adoption. In line with this, (Wolfert et al., 2017) it was also emphasized that big data could help farmers understand weather patterns and production risks and encourage the application of more efficient technology (Kos & Kloppenburg, 2019).

Digitalization also increases supply chain visibility, thereby helping farmers overcome market vulnerabilities. Information technology is crucial in precision agriculture, allowing farmers to make better data-based decisions. This is in line with the results of the analysis, which show that IT positively correlates with the application of agricultural technology.

Furthermore, IT also increases farmers' sensitivity to environmental and market changes, positively correlating with adopting ecological technology, irrigation, and marketing. Farmers' access to information can increase their sensitivity to environmental and market changes. This is a driving factor for adopting appropriate technology. These results also show that farmers more sensitive to change tend to be more proactive in adopting new technologies. This result is supported by research conducted by Klerkx et al. (2019), emphasizing that digital technology can increase farmers' awareness of environmental changes. Rose et al. (2021) explain the role of sensors and IoT in increasing sensitivity to microclimate variations. Meanwhile, access to real-time market information increases farmers' sensitivity to price fluctuations.

Furthermore, IT has been shown to increase farmers' adaptive capacity, with a significant positive effect on adopting environmental technology, irrigation, and marketing. These results show that information technology increases farmers' adaptive capacity by providing access to knowledge and best practices (Fielke et al., 2020). Explain that agricultural digitalization can increase farmers' access to global expertise and encourage farmer innovation.

Farmers with high adaptive capacity can better manage risks, such as climate change, market instability, and socio-economic pressures, which ultimately increase their economic resilience and maintain food supply stability. Increasing farmers' adaptive capacity positively correlates with economic resilience, essential in reducing vulnerability to external shocks (Abdollahzadeh et al., 2023; Xie & Huang, 2021). In addition, Diallo et al. (2020) revealed that more adaptive farmers tend to be better able to maintain consistent food production, even under adverse conditions, directly contributing to food security. This increased adaptability can be achieved through access to technology, education, and policy support that supports agricultural diversification and innovation. Thus, increasing farmers' adaptive capacity is a key strategy to ensure economic and food security, especially in the face of increasingly complex global challenges.

A critical examination of the existing literature reveals significant strides in understanding how technology integration and access to information can enhance farmers' adaptive capacity and economic resilience. Klerkx et al. (2019) underscored the role of digital technology in improving farmers' sensitivity to environmental and market changes. Their findings demonstrate that farmers with better access to information can adopt appropriate environmental technology, irrigation systems, and marketing strategies. This sensitivity to change, supported by information technology, fosters a proactive approach among farmers toward adopting new technologies. However, while Klerkx et al.'s (2019) work highlights the correlation between information access and technology adoption, it falls short of exploring how these factors interact within the broader framework of livelihood capital integration.

Previous studies have made substantial contributions in examining the role of information technology in strengthening farmers' adaptive capacity and reducing vulnerability. For example, Klerkx et al. (2019) and Saiz-Rubio and Rovira-Más (2020) emphasize how digital technologies, sensors, and big data help farmers increase their awareness of climate variability, market dynamics, and production risks. These technologies support informed decision-making, encouraging sustainable environmental, irrigation, and marketing practices. Their work provides a valuable foundation for understanding the transformative potential of digital agriculture.

However, most of these studies emphasize a one-dimensional view, focusing mainly on information flow and technical aspects of technology, without sufficiently exploring the social, cultural, and economic structures determining farmers' ability to adopt these innovations. In other words, they often neglect the role of livelihood capital (human, financial, natural, social, and physical assets), enabling or constraining technology adoption. This is a significant limitation because access to technology does not automatically translate into equitable or practical use, especially among smallholders with different levels of resource endowments (Diallo et al., 2020; Xie & Huang, 2021).

While studies such as Antwi-Agyei and Stringer (2021) highlight the role of technology in increasing adaptive capacity, they generally underexamine how vulnerability perceptions and sensitivity to environmental shocks might influence farmers' technology choices. For example, the finding of a negative relationship between information technology and farmers' sensitivity suggests that excessive reliance on technology could make farmers less responsive to micro-level environmental signals. This area has received limited attention in previous literature.

Furthermore, although Klerkx et al. (2019) and Rose et al. (2021) emphasize that technology increases farmers' sensitivity to market changes and weather variability, they do not fully address the possibility that increased sensitivity could make some farmers more risk-averse and conservative, preferring traditional methods that have worked in the past (Khoza et al., 2021). This creates a paradox: farmers might become more informed but not necessarily more willing to adopt advanced irrigation or marketing technologies, which is consistent with the weak or insignificant relationships found in previous models (Aryal et al., 2020; Wang et al., 2021). Moreover, while much research has proven the effectiveness of adaptive capacity in promoting environmental, irrigation, and marketing technology adoption (Stringer et al., 2020; Serote et al., 2021), few have investigated how adaptive capacity is built collectively within farming communities, or how institutional support, policy incentives, and education shape farmers' innovation ecosystems. Fielke et al. (2020) rightly mention that agricultural digitalization can broaden farmers' knowledge networks, but overlook social barriers such as trust, local knowledge, and farmer-to-farmer diffusion, which can moderate these effects.

CONCLUSION

The results of this study demonstrate that a model incorporating information technology (IT) together with multiple dimensions of livelihood capital can effectively enhance farmers' adaptive capacity, creating more resilient farming communities to confront complex global challenges. IT significantly influences farmers' vulnerability, sensitivity, and adaptation levels, which in turn supports the adoption of environmental, irrigation, and marketing technologies. IT can raise farmers' awareness of the vulnerabilities of their livelihoods to climate change and other agricultural risks and improve their access to high-quality farm information and practices. However, the finding that IT use may reduce farmers' sensitivity to direct environmental signals suggests the need for complementary training and local knowledge strengthening to avoid overdependence on technology.

Farmers' awareness of vulnerability encourages the adoption of improved ecological technologies, such as soil and water conservation practices. However, awareness alone may not be sufficient to drive investments in advanced irrigation and marketing technologies, requiring policy incentives and financial support mechanisms. Higher levels of adaptation capacity positively influence technology adoption, showing that farmers with greater adaptive capacity are more proactive in adopting various technologies to improve productivity and sustainability.

From a policy standpoint, this study provides substantive and actionable recommendations. First, policymakers are advised to prioritize integrating digital literacy programs within agricultural extension services to fully leverage the benefits of information technology while preserving environmental sensitivity. Second, implementing targeted subsidies or credit schemes is recommended to support investments in irrigation and marketing technologies interventions less dependent on vulnerability awareness alone.

Third, fostering farmer-led innovation platforms is essential to promote peer-to-peer knowledge exchange and collectively enhance adaptive capacity. Fourth, developing data-driven early warning systems should be pursued to complement farmers' indigenous knowledge, ensuring that technology empowers rather than displaces traditional coping mechanisms. Lastly, investing in comprehensive programs that synergistically address the strengthening of livelihood assets, adopting appropriate technologies, and climate adaptation strategies under a unified policy framework is imperative.

These insights underscore the critical role of coherent policy and institutional arrangements in advancing the integration of information technology and livelihood capital to reinforce farmers' resilience and food security. Adopting these recommendations by governmental bodies, non-governmental organizations, and development partners will contribute to developing a more resilient, sustainable, and climate-adaptive agricultural sector in East Java and potentially in other comparable regions.

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