AGRISOCIONOMICS
Jurnal Sosial Ekonomi dan Kebijakan Pertanian
ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

FACTORS INFLUENCING SHALLOT FARMERS' DECISION TO ADOPT LIGHT TRAPS IN DEMAK, CENTRAL JAVA

Reza Siskana Lia[1*], Mukson[1], Siwi Gayatri[1], Mochammad Alawy Syaiful Anam[2], and Muhammd Zainul Asror[3]
[1]Agribusiness, Faculty of Animal and Agricultural Sciences, Universitas Diponegoro, Semarang, Central Java, Indonesia
[2]Agribusiness, Faculty of Science, University of Queensland, Gatton, Queensland, Australia
[3]Animal Sciences, Wageningen University & Research, Droevendaalsesteeg, Wageningen, Netherlands

*Correspondence Email: rezasiskanalia00@students.undip.ac.id

Submitted 08 August 2024; Approved 02 October 2024

ABSTRACT

The production of shallots in Demak district in 2019–2023 tends to decline and become less stable, mainly due to plant-disturbing organism attacks. Using chemical pesticides to deal with plant-disturbing organisms can damage soil and cause pest resistance, requiring environmentally friendly technologies such as insect light traps. In adopting light trap technology, it is interesting to study farmers' decision-making processes and the factors influencing them. We conducted the study in January 2024 in Demak District, Central Java, Indonesia, using survey and purposive sampling methods to identify factors influencing farmers' decision-making when using light trap technology to increase shallot productivity. The sample consisted of 165 farmers using light traps, with primary and secondary data. We used Smart-PLS 3.0 software to analyze the variable measurement using a Likert scale (1–5). With path coefficients of 0.460, 0.199, and 0.398, respectively, the study indicated that internal variables, external factors, and innovation features much influenced farmers' choice to adopt light trap technology. With a path coefficient of 0.649, light trap adoption favored agricultural productivity, hence driving a 42.1% rise in output. The model was generally good, with significant predictive power, with a GoF score of 0.65617 and an R-square value of 0.633. Therefore, this study accepts the hypotheses and finds that internal, external, and innovative aspects influence farmers' decision to utilize light traps. This study adds essential theoretical and empirical data and clarifies how smallholder farmers promote sustainable agriculture by using light traps, therefore lowering the usage of chemical pesticides.

Keywords: *light trap, productivity, shallot farmer*

BACKGROUND

Shallot (*Allium ascalonicum L.*) is a horticultural commodity with high economic value and is essential for people's consumption needs in Indonesia (Atman et al., 2021). Shallots are also commercially important in the Amhara region, including the Eastern Gojjam Zone and Ethiopia (Yeshiwas et al., 2023). Homemakers favor shallots as a staple ingredient in their dishes, with no substitutes (Pangestuti et al., 2022). Aside from Indonesia, Persia classifies shallots as vegetables rich in nutritional value and medicinal properties (Bahadorzade et al., 2022). Iran's market demand for shallots as a medicinal industry is also strategic (Amiri et al., 2021).

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

The nutritional value and benefits of shallots make this commodity suitable for intensive cultivation by farmers (Pangestuti et al., 2022). Ethiopia has enormous potential for cultivating horticultural crops in general and vegetables in particular for small-scale and commercial production (Yeshiwas et al., 2023). In many parts of Ethiopia, shallots are the most widely cultivated bulb crop alternative to shallots (Yeshiwas et al., 2023). When planted with a short cycle, shallots exhibit characteristics such as greater disease tolerance and long-term storage with proper treatment (Lou et al., 2022). Some of these things make shallots more favorable to farmers. Shallot farming can create jobs that contribute to the national economy. The importance of shallots leads to potential micro-inflation in Indonesia if the supply is insufficient, especially during non-harvest seasons or religious holidays. Through the Ministry of Agriculture Policy, the government makes various efforts to ensure the availability of shallots throughout the year.

In 2021, shallot production in Indonesia reached 2.01 million metric tonnes, an increase of 10.42% compared to 2020 (Badan Pusat Statistik, 2022). Central Java Province is the nation's largest producer of shallots, with 546.26 thousand tons. Brebes Regency in Central Java is the leading producer, producing 3,410,565 quintals, this was followed by Demak Regency, which produced 587,050 quintals in 2021.

Demak Regency has ranked second only to Brebes Regency as a shallot-producing area in Central Java since the 1970s. In 2022, the shallot harvest area will be 6,748 ha, with a total production of 510,809 quintals. The shallot-producing center in Demak Regency is located in 5 sub-districts, namely Mijen sub-district with an area of 3,303 ha, Karanganyar sub-district with an area of 1,017 ha, Wedung sub-district with an area of 564 ha, Demak sub-district with an area of 424 ha, and Dempet sub-district with an area of 321 ha. Demak Regency's potential is very supportive of shallot cultivation. Demak Regency has a favorable market share, land suitability, and agroecosystems that support optimal growth. However, shallot production in Demak Regency during the 2019–2023 period tended to decline, as shown in Figure 1.

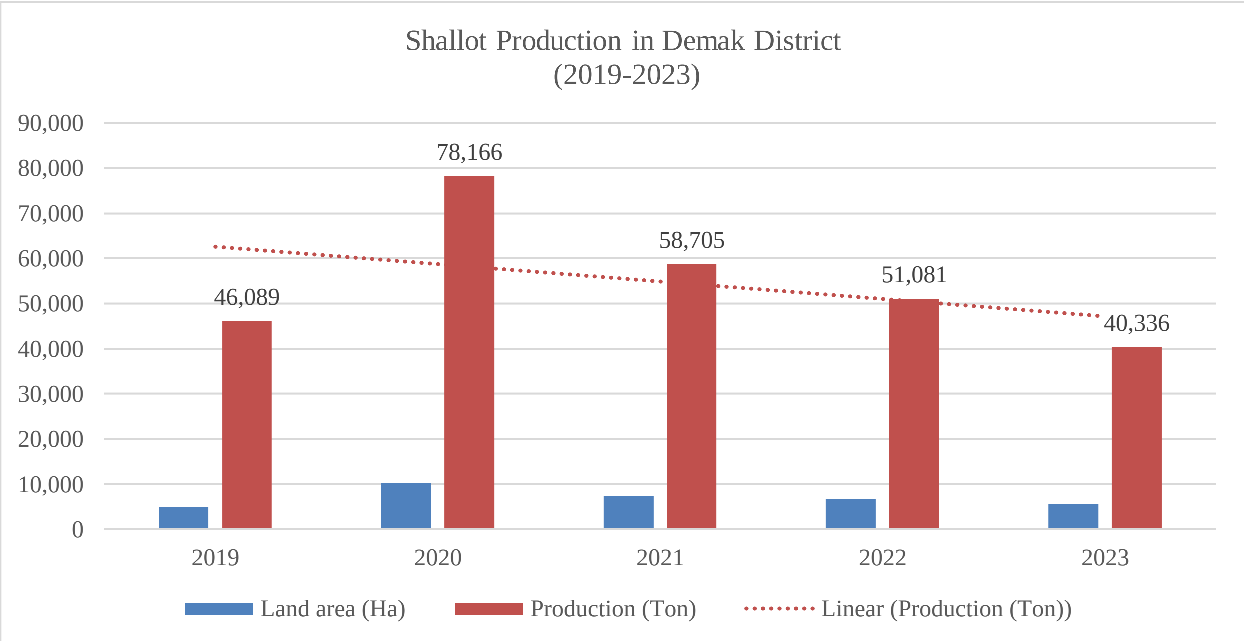

Figure 1. Shallot production in Demak district (2019-2023)
Source: Indonesia Statistics Bureau (2024)

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

The diagram above illustrates the decreasing trend of shallot production in Demak District from 2019 to 2023. Primarily due to the attack of plant-disturbing organisms (Pests) (Atman et al., 2021). The research of Triwidodo and Tanjung (2020) explain that pests like leaf-boring flies (*Liriomyza chinensis*), orong-orong (*Gryllotalpa spp*.), armyworms (*Spodoptera litura*), and thrips (*Thrips tabaci*) make it challenging to grow shallots. Farmers use chemical pesticides to deal with these pests because they are practical, fast, efficient, and effective. Farmers' belief in the efficacy of chemical pest control in Pakistan hinders the adoption of environmentally friendly pest trap technology (Khan et al., 2021). Long-term use of chemical pesticides can damage soil, cause pest resistance, and negatively affect human health and the environment (Ansoruddin et al., 2021). Therefore, we need a more environmentally friendly insect trapping technology to support sustainable agriculture in the future. China has utilized light trap technology on its tea plantations. The reflected light can attract and kill many pests that can damage the ecology of tea gardens (Bian et al., 2018).

In Europe, light traps and chrysanthemum greenhouses were also used as environmentally friendly pest traps. Light can effectively trap the pest *L. rugulipennis* in the greenhouse (Tol et al., 2022). Although very suitable for agriculture due to low input costs, using light traps has a low implementation record in developing countries (Khan et al., 2021). Shallot farmers in Brebes Regency, Indonesia, have implemented pest traps using insect light trap technology (Enriko et al., 2024; Suripto and Anton, 2023). Light traps are devices that use light to attract and capture nuisance pests, thereby reducing pest populations without harming the environment. Onderstepoort's 220-V ultraviolet (UV) light trap effectively captures nuisance pests on South African farms. (de Beer et al., 2021). Venter et al. (2021) conducted similar research and found that UV lamp traps effectively reduce the abundance of Culicoides pests in South Africa. Applying alternative pest control technologies is integral in encouraging sustainable agricultural production (Khan et al., 2021).

Based on previous research, the main discussion focused on using light traps, concentrating only on their effectiveness in suppressing insects (de Beer et al., 2021; Venter et al., 2021). Therefore, this study explores the psychological and social factors influencing farmers' decision to adopt this technology, such as risk perception and level of trust in the technology. Understanding farmers' decision to adopt light traps is complex, as many factors influence it (Khan et al., 2021). In this study, surveys and interviews were used to understand these factors. Roger Everett's Diffusion of Innovations Theory describes five factors influencing technology adoption: relative advantage, compatibility, complexity, trial, and visibility (Michler et al., 2018).

The challenges shallot farmers face in Demak, mainly caused by recurring pest attacks, are a significant obstacle in maintaining stable production. Often, farmers opt for chemical pesticides under the assumption that they are more efficient and quick in eradicating pests, with little consideration of the long-term impacts on the environment and health. These insecticides can cause harm to human health, pest resistance, and soil damage. Farmers still rely on chemicals despite their known dangers because they are affordable and easy to apply; they usually ignore sustainable solutions such as light traps.

Light traps are an essential and eco-friendly way to tackle this pest problem. As demonstrated in European chrysanthemum greenhouses, light traps have successfully captured pests, including Lygus rugulipennis, without causing adverse consequences from chemicals. Similar traps have been used by shallot farmers in Brebes District, Indonesia, to prove how well they reduce pest numbers. The use of UV light traps, such as Onderstepoort's 220-V UV light trap in South Africa, further demonstrates the adaptability of this technique in many farming environments. Although light traps have minimal input costs, are environmentally safe, and conform to sustainable farming methods, adopting this technology still needs to be improved in undeveloped areas such as Central Java. This low acceptance is due to social and psychological factors, including risk perception and trust in the new technology. According to Roger Everett's Diffusion of Innovations Theory, several factors influence adoption decisions, including relative advantage, compatibility with current practices, complexity, and visibility of results. These elements become essential for small-scale farmers with limited resources in deciding whether or not they are ready to change from familiar chemical approaches.

The situation in Demak emphasizes the need for focused action to overcome pragmatic and psychological barriers to light trap acceptance. To ensure successful light trap adoption, stakeholders should raise awareness of the long-term benefits, provide financial assistance or subsidies to make the technology cheaper, and offer training to demonstrate the efficacy of the traps in a natural environment. Light traps can be crucial in solving the insect problems experienced by shallot farmers by bridging the gap between their current methods and sustainable alternatives, thereby supporting more sustainable agriculture in Demak and beyond.

Farmers' considerations include individual capabilities, future constraints, the influence of norms and culture, resources, attitudes, or whether they may prioritize subsistence over profitability (Llewellyn & Brown, 2020). Decisions made by the group can also influence individual farmers' rulings. The interaction between these factors is crucial in shaping farmers' decisions related to their agricultural activities. Innovation adoption has been and continues to be fundamental in efforts to observe technical changes and impacts on the farm sector in developing countries (Glover et al., 2016; Mwinuka et al., 2017; Huffman, 2020).

This study aims to find solutions to the decline in shallot productivity in the Demak district. Farmers have yet to fully adopt light trap technology despite its implementation in the field. Various internal and external factors influence farmers' decisions to adopt or not adopt this technology (Budiman et al., 2024). This study also aims to identify the influence and significant relationship between latent variables (X) and dependent variables (Y). This research employs the diffusion of innovation theory to analyse the adoption of light traps by farmers in Demak Regency, Central Java. Rogers, 1995 popularised this theory; Rogers, 2003.

1. **Hypothesis 1**. Innovation characteristics (X1) significantly affect farmer decision variables (Y1). Research by Kaur et al. (2023) states that relative advantage significantly accelerates farmer adoption compared to other variables. However, factors such as ease of use and observation also have a positive impact. Characteristics of innovations like high relative advantage, compatibility, triability, and observability make it easier for people to use the intercropping system (Foguesatto et al., 2020). Innovation characteristics, including benefits, price, and compatibility, influence farmers' motivation for innovation adoption (Budiman et al., 2024).
2. **Hypothesis 2**. Internal factors (X2) significantly affect farmers' decisions (Y1). Khoza et al. (2019) found in Gauteng Province, South Africa, that factors like education level, farming experience, and age positively influence the decision to participate in the agro-processing program. Higher education levels tend to diversify into more advanced renewal sectors. Other studies have demonstrated that education level and farming experience influence farmer participation in new programs (Herrera et al., 2023; Budiman et al., 2024). The relationship between age and the decision to adopt an update is non-linear, i.e., the increasing age of farmers (up to a certain age)

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

tends to increase the level of adoption. However, after farmers reach a certain age, the participation rate will stagnate (Ngango et al., 2022).

3. **Hypothesis 3**. External factors (X3) significantly affect farmer decision variables (Y1). Agricultural institutional support plays a vital role in farmer adoption of emission reduction innovations (Herrera et al., 2023). External contexts, such as social communities, significantly affect farmers' decision-making for adopting sustainable innovations (Torgerson et al., 2023). Research by Foguesatto et al. (2020) and Arhin et al. (2024) shows that social dynamics actively and significantly guide farmers' decision-making decisions.
4. **Hypothesis 4**. The farmer decision variable (Y1) affects farmer productivity (Y2). An individual's innovation decision-making process involves five stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 2003; Teye et al., 2024). Farmers' knowledge and perceptions play an intrinsic role in influencing innovation adoption decisions. Farmers' decisions to adopt intensification practices affect income increases and productivity improvements (Hinojosa et al., 2018).

RESEARCH METHODS

Study Location

Research for the study was conducted in Pasir, Bantengmati, and Gempolsongo villages in the Mijen sub-district of Demak (Figure 2). Following Brebes District in Central Java Province, we decided on Demak as the district to apply light trap technology for shallot farming. Within the Mijen sub-district, the Pasir, Bantengmati, and Gempolsongo villages were chosen based on their strategic importance to shallot growing. These communities show different degrees of light trap technology adoption, which enables an all-encompassing study of early adopters and those still opposed to the technology. Their geographic and agroecological conditions—land size, resource access, and pest challenges—also fit the study's goals by offering various agricultural methods and production levels. Targeting farmers who have employed light trap technology was done using a purposive sample approach. This approach guarantees that the sample corresponds with the study's aim of identifying the elements affecting the acceptance of this particular technology. Focusing on farmers who currently use light traps helps us lower sample bias and ensure that the data gathered aligns with actual experiences, enhancing our results' validity.

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

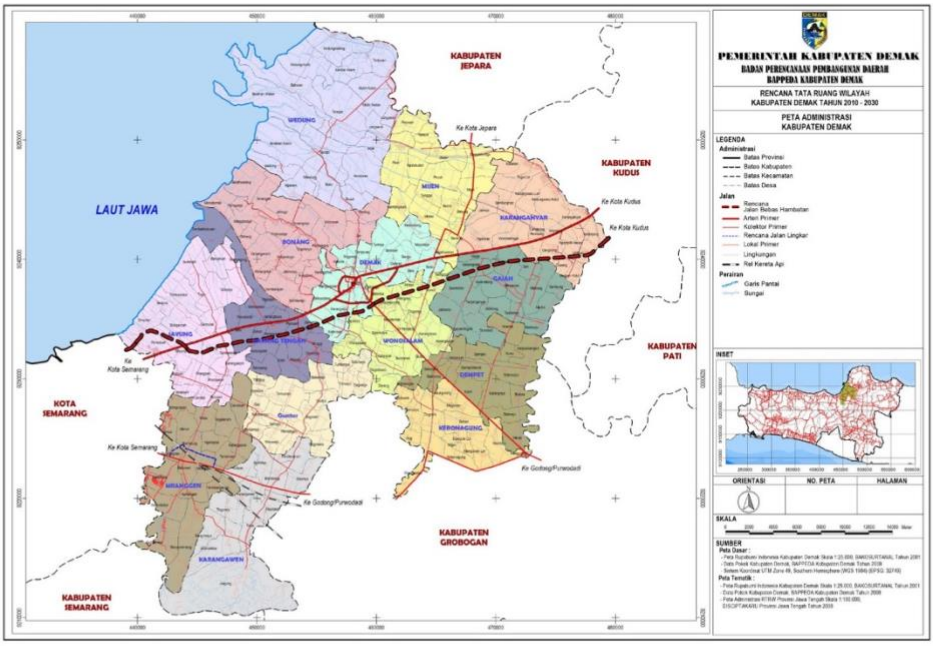

Figure 2. Demak Regency Administration Map
Source: Indonesia Statistics Bureau (2022)

Data Types and Data Collection Techniques

Data types and techniques: We collected primary data through interviews and direct observation using pre-prepared questionnaires. This included information about farmer characteristics, land area, farming experience, types of shallots planted, cultivation techniques, production, business productivity, and decision-making processes and factors in the 2023 production season. We measured internal, external, and innovation characteristics (exogenous variables) and the decision to use light trap technology and farm productivity (endogenous variables) using a Likert scale with a scoring range of 1 to 5. We obtained secondary data supporting the research from the Demak District Agricultural Extension Office (BPP), the Directorate General of Horticulture, the Demak District Badan Pusat Statistik, and the Demak District Agriculture Office. Furthermore, the sample is determined intentionally (incidental sampling) for farmers who adopt light trap technology in shallot farming. The Taro Yamane formula determined the number of samples, with a value of d2 = 7.5%. Researchers used a sample of 165 shallot farmers who had used light trap technology.

Data Analysis

The research data were analyzed Structural Equation Model-Partial Least Square (SEM-PLS) with SMART PLS 3.0 software to analyze the research data. Smart PLS, a multivariate statistical method, simultaneously tests the relationship between variables for prediction, exploration, or structural model development (Hair et al., 2019). Without making assumptions about the data distribution, PLS-SEM allows you to estimate complex models with numerous building blocks, indicator variables, and structural paths. Researchers often recommend this method for prediction rather than hypothesis testing, mainly when the sample size is small or the data contains significant noise (Ringle et al., 2012; Hair et al., 2019). We chose Smart PLS for analysis because it does not require certain assumptions about data distribution and can effectively handle complex models. The model used in this study includes the following variables; 1) decision to use light trap technology (Y1

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

), knowledge stage (Y1.1), persuasion stage (Y1.2), decision making stage (Y1.3), implementation stage (Y1.4), confirmation stage (Y1.5); 2) farm productivity (Y2), land area (Y2.1), labor (Y2.2), input costs during the growing season (Y2.3); 3) innovation character (X1), relative advantage (X1.1), suitability (X1.2), complexity (X1.3), trial (X1.4), observation (X1.5); 3) internal factors (X2), farmer age (X2.1), farmer education level (X2.2), farming experience (X2.3); 4) external factors (X3), demonstration plots (X3.1), extension services (X3.2), farmer groups (X3.3), and government assistance (X3.4) (Figure 3).

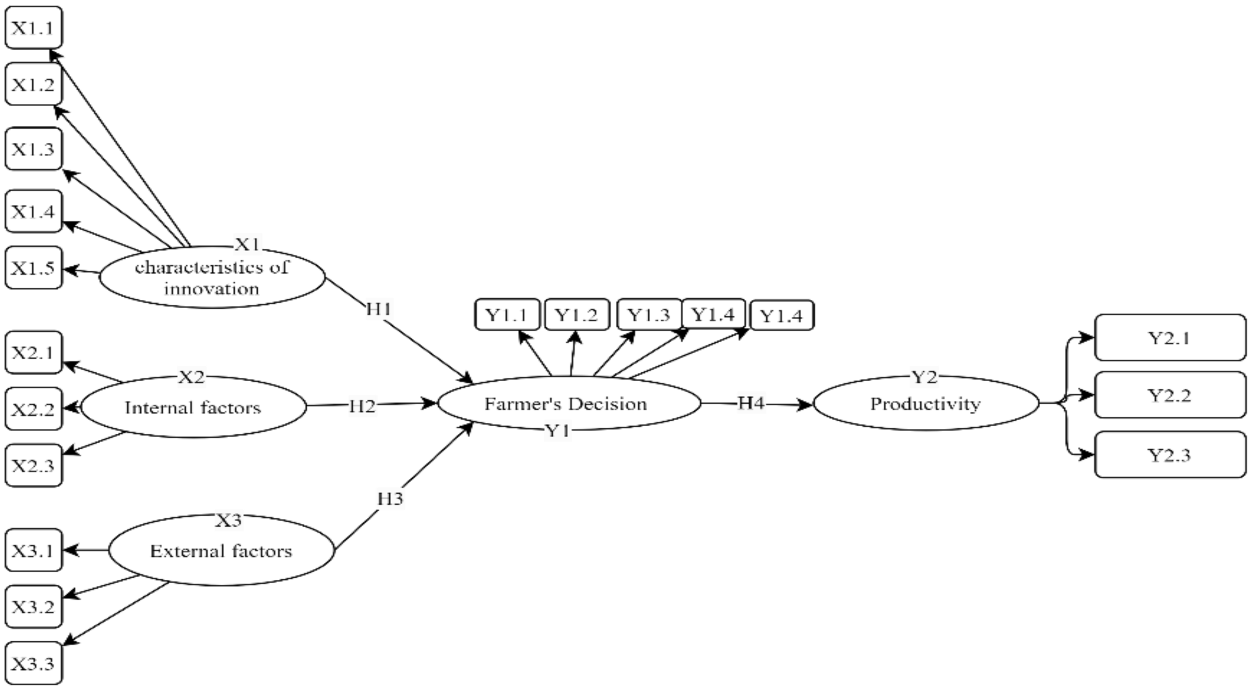

Figure 3. Model Fit SEM-PLS Analysis
Source: Primary Data Analysis (2024)

External Model Measurement

Measurement models are used to assess the reliability and validity of data (Ringle et al., 2012). The scale's internal consistency reliability was measured using Cronbach Alpha and composite reliability. All constructs' CA and CR values were more than 0.7, indicating excellent scale reliability. We evaluated indicator reliability using the criterion that the loading value should exceed 0.70 (Hair et al., 2019). Construct validity includes two fundamental aspects, namely convergent validity and discriminant validity. Convergent validity measures the extent to which the construct converges to explain the variance of its items, which is determined by the average variance extracted (AVE) (Hair et al., 2011). Discriminant validity is the degree to which a construct can be empirically distinguished from other constructs in the structural model. This validity is examined using two criteria, namely the Fornell-Larcker criterion and the cross-loading criterion (Hair et al., 2019).

Structural Model

Before assessing the structural model, one should test for collinearity to ensure the unbiasedness of the regression results (Hair et al., 2019). Often used to evaluate collinearity, the variance inflation factor (VIF) fell between 1 and 4.1, below the threshold of 5 (Hair et al., 2019). This indicates that there are no significant collinearity issues. Bootstrapping is a nonparametric method that checks the statistical significance of different PLS-SEM results. It was used to look at

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

path coefficients (β), Cronbach's alpha values and R^2 were assessed through the PLS Algorithm (which is essentially a regression series in terms of weight vectors) and Bootstrapping (a nonparametric procedure that allows testing the statistical significance of various PLS-SEM results) (Ghozali & Latan, 2015).

This work selected Structural Equation Modelling-Partial Least Square (SEM-PLS) because of its robustness to non-normal data and capacity to control complicated models with limited samples. For a study including several constructs and indicators, SEM-PLS is perfect since it permits simultaneous estimates of several relationships between variables. Nevertheless, SEM-PLS has restrictions mainly in that it emphasizes more prediction than theory testing, which can limit the capacity to verify theoretical links. Furthermore, SEM-PLS does not offer global goodness-of-fit indices like covariance-based SEM techniques, which is a disadvantage in the evaluation of general model fit (Hair et al., 2019; Sarstedt et al., 2022; Henseler et al., 2016). The findings produced are also highly dependent on data quality.

RESULT AND DISCUSSION

Respondent Characteristics

This study included several farmer respondents who have used or are currently using the light trap technology during Planting Season 3 (MT 3), which runs from June to July. Table 1 presents some characteristics of the respondents based on age, education level, length of farming, land size, and land ownership status.

Table 1. Respondent Characteristics

Respondent Characteristics	Number (Person)	Percentage (%)
Age (year)		
15 – 54	74	44.85
>54	91	55.15
Education Level		
Did not finish school	10	6.06
Primary School	112	67.88
Junior High School	24	14.54
High School	10	6.06
Higher Education	9	5.45
Length of Farming (Years)		
< 5 years	2	1.21
5 - 10 years	13	7.88
>10 years	150	90.9
Land Area (Hectares/Ha)		
<0.5 Ha	80	48.48
0.5 - 1 Ha	61	36.97
>1 Ha	24	14.55
Land Ownership Status		
Personal	78	47.27
Rent	87	52.73

Source: Primary Data Analysis (2024)

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Based on primary data in 2024, 74 respondents (44.85%) were in the productive age for farming. Age is important for farm productivity because it affects physical abilities and ways of thinking about solving problems. Saputro & Sariningsih (2020) state that the productive age of farmers is 15–54, and in this age range, farmers are able to provide maximum results. Sholeh et al. (2021) support this by stating that people of productive age have more energy than those below or above this age range.

Table 1 reveals that most shallot farmers in Demak District, specifically 112 respondents (67.88%), have only completed formal education up to the primary school level. Rogayah & Mala (2018), Prasetya & Putri (2019), and Saputro & Sariningsih (2020) indicate that more education is needed to support the quality of farmers' human resources. According to farming experience, most shallot farmers in Demak district (90.9% of 150 respondents) have more than ten years of experience. This experience increases knowledge, skills, and decision-making related to new technologies. According to research by Asfiati & Sugiarti (2021), experience encourages openness to innovation, but external factors also influence innovation acceptance.

The size of cultivated land is another essential characteristic. The majority of farmers own <0.5 ha (48.48% or 80 respondents), while 36.97% (61 respondents) own 0.5–1 ha, and 14.55% (24 respondents) own >1 ha. Larger plots of land carry a higher risk of pest attack, prompting the use of technologies like light traps to mitigate this risk. However, small-scale farmers also use this technology. Private and rented land have different ownership statuses. 52.73% of farmers rent land, usually from the village government with an annual auction system, with rental fees ranging from RP 10,000,000 to RP 15,000,000 per bahu (0.7 ha) per year. The remaining 47.27% cultivate privately owned land from inheritance or purchase.

Measurement Model (Outer Model)

The first step is to check whether the model has convergent validity by evaluating whether the *loading factor* index of each construct meets the validity criteria. Validity was tested using the path diagram from Smart PLS 3, and the configuration results are shown in Figure 4.

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

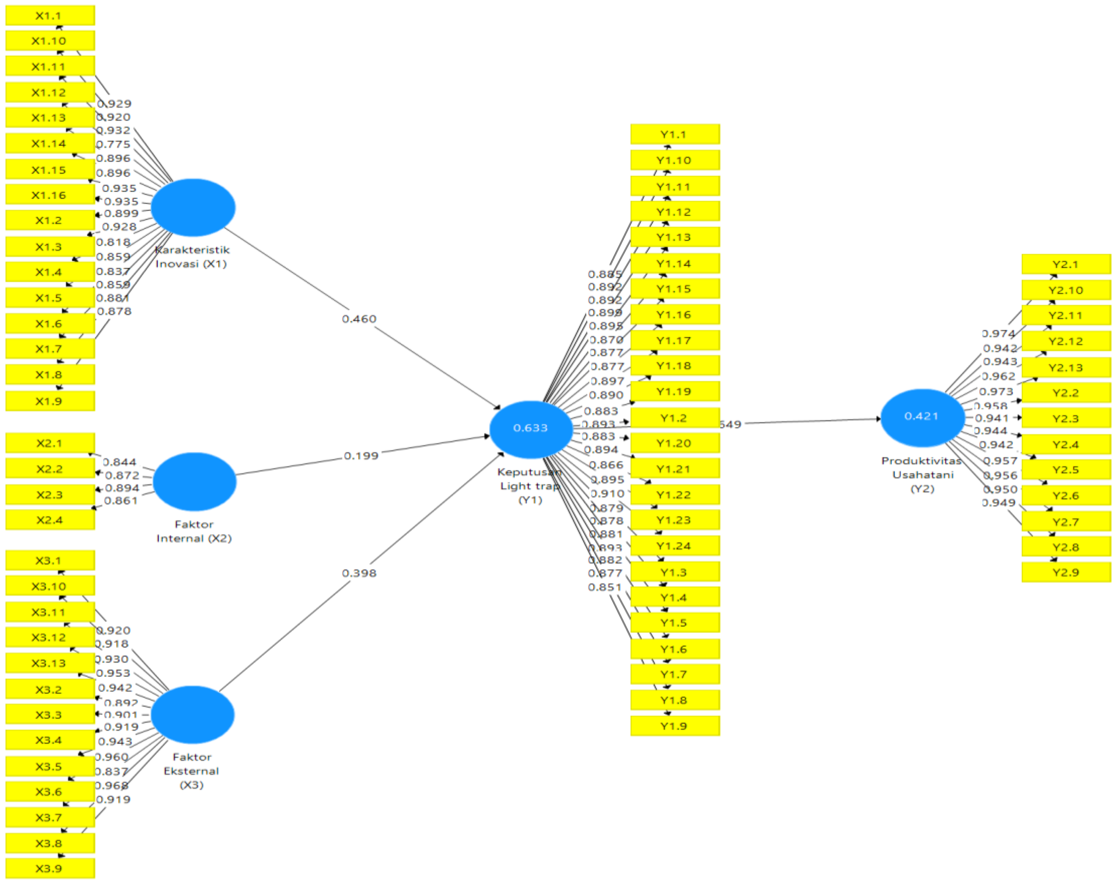

Figure 4. Outer Model
Source: Primary Data Analysis (2024)

Based on the construct diagram analysis results, all indicators in this study have a correlation value above 0.7, indicating that the indicators are valid and accepted for further analysis. The variable indicators of innovation characteristics, internal factors, external factors, decision to use light trap, and farm productivity have a loading factor above 0.70, according to the validity criteria of Ghozali and Latan (2015). However, the correlation value between variables such as innovation characteristics with the decision to use light trap is 0.460, internal factors with the decision to use light trap is 0.199, external factors with the decision to use light trap is 0.398, and the decision to use light trap with farm productivity is 0.649.

Convergent Validity

The convergent validity test results produce the loading factor value of each indicator and construct. Table 2 presents the following output results.

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Table 2. Outer Loading Factor (Convergent Validity)

	X1	X2	X3	Y1	Y2
X1.1	0.929				
X1.10	0.920				
X1.11	0.932				
X1.12	0.775				
X1.13	0.896				
X1.14	0.896				
X1.15	0.935				
X1.16	0.935				
X1.2	0.899				
X1.3	0.928				
X1.4	0.818				
X1.5	0.859				
X1.6	0.837				
X1.7	0.859				
X1.8	0.881				
X1.9	0.878				
X2.1		0.844			
X2.2		0.872			
X2.3		0.894			
X2.4		0.861			
X3.1			0.920		
X3.10			0.918		
X3.11			0.930		
X3.12			0.953		
X3.13			0.942		
X3.2			0.892		
X3.3			0.901		
X3.4			0.919		
X3.5			0.943		
X3.6			0.960		
X3.7			0.837		
X3.8			0.968		
X3.9			0.919		
Y1.1				0.885	
Y1.10				0.892	
Y1.11				0.892	
Y1.12				0.899	
Y1.13				0.895	
Y1.14				0.870	
Y1.15				0.877	
Y1.16				0.877	
Y1.17				0.897	
Y1.18				0.890	
Y1.19				0.883	
Y1.2				0.893	
Y1.20				0.883	
Y1.21				0.894	
Y1.22				0.866	

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

	X1	X2	X3	Y1	Y2
Y1.23				0.895	
Y1.24				0.910	
Y1.3				0.879	
Y1.4				0.878	
Y1.5				0.881	
Y1.6				0.893	
Y1.7				0.882	
Y1.8				0.877	
Y1.9				0.851	
Y2.1					0.974
Y2.10					0.942
Y2.11					0.943
Y2.12					0.962
Y2.13					0.973
Y2.2					0.958
Y2.3					0.941
Y2.4					0.944
Y2.5					0.942
Y2.6					0.957
Y2.7					0.956
Y2.8					0.950
Y2.9					0.949

Source: Primary Data Analysis (2024)

The statistical analysis results show that all factor loading values exceed 0.70, with the lowest loading value of 0.775 and the highest at 0.974. Therefore, each indicator has fulfilled its convergent validity. Ghozali & Latan (2015) state that research indicators with a factor loading value > 0.70 are considered valid and can proceed to the following analysis stage, which aligns with our results. Therefore, we can conclude that the indicators in this study are valid and satisfy the convergent validity requirements.

Discriminant Validity Test

The Discriminant Validity Test results show the Fornell-Lacker Criterium value and AVE value for each indicator. The output is presented in Tables 3 and 4.

Table 3. Fornell-Larcker Criterium

	External Factors (X3)	External Factors (X3)	External Factors (X3)	External Factors (X3)	External Factors (X3)
External Factors (X3)	0.924				
Internal Factors (X2)	0.130	0.868			
Innovation Characteristics (X1)	0.129	0.850	0.887		
Light Trap Decision (Y1)	0.483	0.642	0.680	0.885	
Farm Productivity (Y2)	0.445	0.334	0.364	0.649	0.953

Source: Primary Data Analysis (2024)

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Based on Table 3, the analysis results show that all constructs fulfill discriminant validity. The square root of AVE for the internal factors (0.868), innovation characteristics (0.887), light trap decision (0.885), and farm productivity (0.953) variables are each greater than the inter-construct correlation value. These Fornell-Lacker Criterium values indicate that the discriminant validity requirements have been met, consistent with the findings of Kirana and Mulyana (2022). Thus, these results provide confidence that the research model can be effectively applied in decision-making related to farm adoption and productivity and in designing more accurate and relevant strategies to improve farm efficiency and yield. To see the validity of the differentiators, we can examine the square root value of the Average Variance Extracted (AVE), which is recommended to be greater than 0.5. Table 4 below presents the AVE values in this study.

Table 4. Average Value of Extracted Variance

Variables	Average Variance Extracted (AVE)
Innovation Characteristics (X1)	0.787
Internal Factors (X2)	0.753
External Factors (X3)	0.853
Light Trap Decision (Y1)	0.783
Farm Productivity (Y2)	0.909

Source: Primary Data Analysis (2024)

Table 3 shows that all variables' AVE values exceed 0.5, with innovation characteristics 0.787, internal factors 0.753, external factors 0.853, light trap decision 0.783, and farm productivity 0.909. According to Kirana and Mulyana (2022), this indicates that all variables fulfill good convergent validity by the standard >0.50, so the research results can be considered reliable for further analysis.

Reliability Test

The reliability test results indicate that Cronbach's alpha value for each variable, X and Y, is more significant than 0.70. The Cronbach's alpha value for the innovation characteristics variable is 0.982, while the values for internal and external factors are 0.891, 0.986, 0.988 for the light trap decision, and 0.992 for farm productivity. The obtained value meets the reliability requirements of >0.7, indicating the reliability or consistency of the study's variables (Hair et al., 2019). At this stage, the data in the survey can confidently advance to the following analysis, specifically the structural model test. In line with Sayyida (2023), after the constructs in the study pass the validity and reliability tests, the test can proceed to the structural model test. Generally, the statistical analysis reveals a composite reliability value exceeding 0.70, indicating that each variable's composite reliability value satisfies the reliability standard. This suggests that the data exhibits consistency, stability, accuracy, and high predictive power (Aditya et al., 2024).

Structural Model (Inner Model)

Path Coefficient

The statistical analysis results show that each variable in the sample has an original value, indicating a positive overall path coefficient value. The following is a more detailed explanation:

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

1. X1 on Y1 has a path coefficient value of 0.460 with a P-value of 0.000. This shows that the effect of X1 (innovation characteristics) on Y1 (light trap decision) is positive and significant.
2. X2 on Y1 has a path coefficient value of 0.199 and a P-value of 0.014. This shows that the effect of X2 (internal factors) on Y1 (light trap decision) is positive and significant.
3. X3 on Y1 has a path coefficient value of 0.398 and a P-value of 0.000. This shows that the effect of X3 (external factors) on Y1 (light trap decision) is positive and significant.
4. Y1 to Y2 have a path coefficient value of 0.649 with a P-value of 0.000. This indicates that the effect of Y1 (the light trap decision) on Y2 (farm productivity) is positive and significant.

R-Square

The statistical analysis results indicate that the R-square value for variable Y1 is 0.633. This means that innovation characteristics (X1), internal factors (X2), and external factors (X3) explain 63.3% of the variation in the light trap decision (Y1). Other variables that are outside the scope of this study describe the rest. Also, the R-square value for the Farm Productivity variable (Y2) is 0.421, which means that the light trap decision (Y1) is responsible for 42.1% of the variation in farm productivity (Y2). Factors beyond the scope of this study cause the remaining variation. Therefore, we can conclude that this construction model belongs to the moderate or average category. This aligns with the opinion of Firmasyah (2022), which states that the R-square value in the reliability category is 0.67, including high; 0.33, including moderate; and 0.19, including weak.

f-Square

The statistical analysis results show that each exogenous variable's f-square value or effect size on endogenous variables ranges from low to high categories. Hair et al. (2019) categorized the f-square value into three levels of influence: low = 0.02, medium = 0.15, and high = 0.35. The f-square value for X1 (innovation characteristics) on Y1 (light trap decision) is 0.160, which falls into the medium category. The f-square value for X2 (internal factors) on Y1 (light trap decision) is 0.030, which is in the low category. The f-square value for X3 (External Factors) on Y1 (light trap decision) is 0.423, which is in the high category. The f-square value for Y1 (light trap decision) and Y2 (farm productivity) is 0.726, which is in the high category.

Goodness of Fit Evaluation

The evaluation of the goodness of fit reveals that the Q-value is greater than 0, precisely 0.489 for the light trap decision variable (Y1) and 0.380 for the farm productivity variable (Y2). This indicates that the model has excellent predictive relevance. So, we can say that the innovation characteristics (X1), internal factors (X2), and external factors (X3) are all helpful in predicting the light trap decision (Y1) and farm productivity (Y2). A Q^2 value greater than 0 indicates that the model has predictive relevance. According to Hair et al. (2019), the interpretation of the Q^2 value qualitatively is 0 (low influence), 0.25 (moderate influence), and 0.50 (strong influence). The last test is to find the *Goodness of Fit* (GoF)*Index* value, which is used to validate the overall structural model. The GoF value is calculated manually using the following steps:

$$\text{GoF} = \sqrt{(\text{Average AVE}) \times (\text{Average } R^2)}$$

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

$$\text{GoF} = \sqrt{\left(\frac{0{,}787+0{,}753+0{,}853+0{,}783+0{,}909}{5}\right)\times\left(\frac{0{,}633+0{,}421}{2}\right)}$$

$$\text{GoF} = \sqrt{0{,}430559}$$

$$\text{GoF} = 0.65617$$

The analysis results show that the GoF Index value is 0.65617. This value is included in the high category or good fit. According to Syahidah and Aransyah (2023), the interpretation of the GoF Index value is divided into three categories: low fit = 0.1, moderate = 0.25, and high = 0.36.

Hypothesis Test

After testing the data, the next step is to test the hypothesis. Pay attention to the significance value, t-statistic, and p-value to decide whether the hypothesis is accepted or rejected. The hypothesis is accepted if the t-statistic > 1.96 and p-value < 0.05 (Kirana & Mulyana, 2022). The results of hypothesis testing are presented in Table 5.

Table 5. Output of t-Statistic Test

	t Statistics (|O/STDEV|)	**P Values**
Innovation Characteristics (X1) -> Light Trap Decision (Y1)	5.069	0.000
Internal Factors (X2) -> Light Trap Decision (Y1)	2.471	0.014
External Factors (X3) -> Light Trap Decision (Y1)	7.051	0.000
Light Trap Decision (Y1) -> Farm Productivity (Y2)	11565	0.000

Source: Primary Data Analysis (2024)

The relationship between innovation characteristics (X1) and light trap decision (Y1) has a t-statistic value of 5.069, which means the t-statistic value> 1.96 and a *p-value* of 0.000, so that the *p-value* <0.05. This indicates that the first hypothesis innovation characteristics have a significant effect on the decision to use light trap can be accepted.

The relationship between internal factors (X2) and light trap decisions (Y1) has a t-statistic value of 2.471, which means that the t-statistic value is> 1.96, and the *p-value is* 0.014, so the *p-value is* <0.05. This shows that the second hypothesis, internal factors have a significant effect on the decision to use light trap can be accepted.

The relationship between external factors (X3) and light trap decision (Y1) has a t-statistic value of 7.051, which means the t-statistic value> 1.96 and a p-value of 0.000 so the p-value <0.05. This indicates that the third hypothesis external factors have a significant effect on the decision to use light trap can be accepted.

The relationship between light trap decision (Y1) and farm productivity (Y2) has a t-statistic value of 11.565, which means the t-statistic value > 1.96 and a p-value of 0.000, so the p-value < 0.05. This shows that the fourth hypothesis the decision to use light trap has a significant effect on increasing farm productivity can be accepted.

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

The Effect of Innovation Characteristics on Light Trap Decisions

Influence of characteristics of innovation on decision on light trap adoption indicated by a t-statistic of 5.069 (higher than 1.96) and a very significant p-value of 0.000 (less than 0.05), the results of this study unambiguously illustrate that Innovation Characteristics significantly influence the choice to deploy light traps. This suggests, in keeping with the first hypothesis, that the more developed and dynamic the Innovation Characteristics associated with light traps are, the more likely the adoption of this technology in shallot farming is. This result also supports earlier studies, as demonstrated by Nugroho & Widiarti (2021), who discovered that innovative characteristics favorably influence innovation adoption among university students. In line with that, a study by Damayanti et al. (2021) indicated that innovative characteristics like relative advantage, compatibility, trialability, and observability of benefits play a crucial role in accelerating innovation adoption, including in the framework of green hospitals. More generally, these results contribute to the theoretical knowledge of the elements influencing the acceptance of innovation. They show their possible use, especially in hastening the spread of green technologies in the agricultural sector. Stated differently, making sure that inventions like light traps have significant relative advantages and simplicity of use will assist them in being adopted and used on a larger scale, enabling farmers to raise yields and efficacy of shallot production. This work provides essential contributions from a theoretical and pragmatic standpoint in the field.

Influence of Internal Factors on Light Trap Decisions

Internal factor variables, such as age, education level, and farming experience, significantly affect the decision to use light traps. This is indicated by a t-statistic value of 2.471 (t-statistic > 1.96) and a p-value of 0.014 (p-value < 0.05). The higher the value of internal factor variables, the more likely farmers are to adopt valuable technologies. Thus, the second hypothesis, stating internal factors significantly influence the decision to use light trap is accepted. These results are supported by research by Renu & Christe (2018), Khawaja & Alharbi (2021), and Chin (2021) in Nurmelia & Lestari (2022), which show that age, as an internal factor, affects investment decisions. Experience that increases with age and a higher level of education improves one's ability to evaluate options and make profitable decisions. For shallot farmers in Demak, these internal factors play a critical role in technology adoption. Age, for example, is significant because older farmers in Demak, with their accumulated experience in farming, may have a more nuanced understanding of pest management challenges and the benefits of new technologies like light trap. Their extensive knowledge can make them more receptive to innovative solutions that promise to enhance their crop yields and reduce pest-related losses.

Education level is another crucial factor. Shallot farmers with higher levels of education are generally better equipped to comprehend the technical aspects of light trap technology and evaluate its potential benefits. This improved understanding enables them to make more informed decisions about integrating light trap into their pest management practices. Farming experience further influences the adoption of light trap. Experienced shallot farmers in Demak with practical pest control knowledge will likely appreciate the value of a technology that offers effective pest management solutions. Their hands-on experience allows them to assess the feasibility and effectiveness of light trap more accurately, making them more likely to adopt it. In conclusion, understanding the impact of internal factors such as age, education level, and farming experience is essential for promoting the adoption of light trap technology among shallot farmers in Demak. These factors help explain why

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

some farmers are more inclined to adopt innovative pest control solutions, thereby improving overall agricultural practices in the region.

Influence of External Factors on Light Trap Decisions

The study indicates that external factors—such as demonstration trials, extension services, farmer groups, and government assistance—significantly influence the decision of shallot farmers in Demak to adopt light trap technology. With a t-statistic value of 7.051 and a p-value of 0.000, these results confirm that higher values of external factors correspond to a greater likelihood of adopting light trap technology, thereby supporting the third hypothesis that external factors significantly influence the decision to use light trap in Demak, demonstration trials are crucial in influencing adoption decisions among shallot farmers. These trials provide farmers a hands-on opportunity to see how light trap works. Farmers gain concrete evidence of the technology's benefits by observing its effectiveness in managing pests. Successful demonstration trials can build trust and confidence in light trap, making farmers more likely to adopt it widely. Extension services are also vital in Demak. Field Extension Officers (in Bahasa called PPL) act as educators, motivators, and facilitators in agricultural development. They help farmers understand how to use light trap technology, provide necessary training, and offer technical support. Research by Khairunnisa et al. (2021) highlights the critical role of PPL in disseminating agricultural innovations. In Demak, active and supportive PPL can significantly enhance the adoption of light trap by ensuring that farmers receive the information and support they need. Farmer groups in Demak further influence adoption decisions. These groups provide a platform for farmers to discuss their experiences with light trap, share successes, and learn from each other. Dynamic and active farmer groups can facilitate quicker adoption of new technologies by creating a community of practice that supports and encourages the use of light trap. Feriadi et al. (2022) found that support from farmer groups impacts the decision to continue using new agricultural technologies, which applies to the situation in Demak.

Government assistance also affects Demak's adoption decisions through policies, incentives, or support programs. Government programs that provide subsidies, grants, or other support for environmentally friendly technologies like light trap can motivate farmers to adopt these innovations. Research by Setiawan et al. (2022) shows that extension approaches involving demonstration plots and group meetings make extension activities more diverse and influential. In summary, external factors such as demonstration trials, extension services, farmer groups, and government assistance are crucial for adopting light trap technology among shallot farmers in Demak. Enhancing the effectiveness of these external factors can accelerate the adoption process, leading to improved pest management and increased productivity in shallot cultivation in the region.

Effect of Light Trap Decision on Farm Productivity

The results showed that the light trap decision variable had a significant influence on increasing farm productivity, with a t-statistic value of 11.565 (t-statistic > 1.96) and a p-value of 0.000 (p-value < 0.05). In other words, the higher the decision to adopt light trap, the higher the productivity. Thus, the fourth hypothesis, the decision to use the light trap has a significant effect on increasing farm productivity is accepted. Using light trap can increase the effectiveness of input costs and labor on the land. Hartanto (2022) states that adopting renewal technology, such as social media, can reduce promotion and marketing costs and expand market reach. This is in line with the research of Sihombing et al. (2023), which shows that increasing shallot productivity depends on the

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

absorption and implementation of selected innovations. Increased productivity from applying technology will increase farmers' income and facilitate production activities so that farming families can achieve welfare. A similar opinion is also supported by Elvina & Wardhana (2024), who found that social media adoption has a positive and significant effect on improving the performance of MSMEs.

For Demak's shallot farmers, light traps directly relate to better harvests. Two pests that can substantially lower crop output, armyworms and thrips, are pretty sensitive to shallots. Using light traps helps farmers control pests, gradually lowering the need for chemical pesticides. Furthermore, Demak shallot farmers can save money commonly paid for buying pesticides and regular spraying of laborers. Using farmers' profit margins can also support more sustainable and efficient agricultural techniques through reduced input costs. The savings from pest control tools let farmers focus on other production areas, such as enhancing irrigation control or soil quality, eventually increasing crop yields. Should light trap technology be applied to boost output, Demak's shallot growers would likewise be able to produce more. Additionally, it improves local agriculture's sustainability and agricultural families' welfare.

CONCLUSION AND SUGGESTION

Research results conclude that innovation's internal, external, and creative aspects greatly influence farmers' choice to apply light trap technology. The adoption of this technique considerably raises agricultural output. These elements significantly contribute to increasing production efficiency and output in shallot farming. Using technology like light trap can help enhance farmer welfare and sustainable agriculture effectively. The following policy suggestions are meant to assist these conclusions:

1. The government and affiliated parties must enhance their extension and mentorship initiatives for farmers. The main emphasis of this program should be on proving the advantages of light trap technology through field demonstrations and valuable seminars. This project can help farmers adopt technologies by offering practical expertise and addressing their worries.
2. The first investment expenses for farmers implementing the light trap can be lowered through targeted financial support using economic incentives or subsidies. Grants, low-interest loans, or subsidies for technology purchases are three ways this help might appear.
3. Policies must promote research and development of agricultural technologies since they strengthen this field. This covers financing for research institutes and the creation of alliances between agricultural extension agencies, technology developers, and researchers.
4. Creating an enhanced policy framework that generates an environment fit for technology acceptance is vital. This might entail streamlining the legal system, giving digital companies tax breaks, and laying forth unambiguous rules on technology use.

Implementing these policies could present difficulties, including farmers' opposition to change, insufficient funds, and poor extension systems. Strategies including involving local leaders to assist technology adoption, guaranteeing effective resource allocation, and infrastructure enhancement investment should be considered to overcome these obstacles. Future studies should investigate other elements in adopting technology, including farmers' degree of education, information availability, government backing, and social networks. Examining these factors can help one grasp the possibilities and obstacles of modern agricultural technologies. This study significantly

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

adds to the theoretical and empirical literature about smallholder farmers' adoption of light trap technology to lower chemical pesticide use. Though concentrated in Demak District, Central Java, the results apply to other developing areas wishing to raise the welfare of smallholder farmers using sustainable farming methods. This study also closes a gap in the literature by pinpointing essential elements influencing the acceptance of light trap technology, providing insightful empirical data for subsequent studies and policy formulation.

ACKNOWLEDGMENT

Our deepest gratitude to the Lembaga Pengelola Dana Pendidikan (LPDP) for the support and funding provided for this research. Assistance from the LPDP was instrumental in the smooth implementation of the research and data collection. We hope that the results of this research can positively contribute to the development of agriculture in Indonesia.

REFERENCES

Aditya, G., Syafruddin, & Anggra, A. (2024). Tingkat Pengetahuan Petani dalam Pengendalianhama dan Penyakit Tanaman Kakao di Kecamatan Masambaluwu Utara. Jurnal Ilmiah Membangun Desa dan Pertanian (JIMDP), 9(1), 80-90. doi:http://dx.doi.org/10.37149/jimdp.v9i1.835

Amiri, Z., Asgharipour, M. R., Campbell, D. E., Azizi, K., Kakolvand, E., & Moghadam, E. H. (2021). Conservation agriculture, a selective model based on emergy analysis for sustainable production of shallot as a medicinal-industrial plant. Journal of Cleaner Production, 292, 1-19. doi:https://doi-org.proxy.undip.ac.id/10.1016/j.jclepro.2021.126000

Ansoruddin, A., Hasibuan, S., & Pane, H. (2024). Penggunaan Kotoran Sapi dan Limbah Rumah Tangga sebagai Pupuk Organik dalam Upaya Pengurangan Penggunaan Pupuk Kimia. Community Development Journal: Jurnal Pengabdian Masyarakat, 5(1), 2622-2626. doi:https://doi.org/10.31004/cdj.v5i1.26177

Arhin, I., Yeboah, E., Liu, X., Liu, A., Chen , X., & Li, X. (2024). Integrating farmers' perception of sustainable agricultural technologies towards the development of sustainable tea production in China. International Journal of Agricultural Sustainability, 22(1), 1-19. doi:https://doi.org/10.1080/14735903.2024.2303886

Asfiati, R. F., & Sugiarti, T. (2021). Motivasi Petani dalam Usahatani Pembibitan Padi (Studi Kasus di Desa Ngumpak dalem Kecamatan Dander Kabupaten Bojonegoro). Jurnal Ekonomi Pertanian dan Agribisnis (JEPA), 5(3), 735-747. doi:https://doi.org/10.21776/ub.jepa.2021.005.03.12

Atman, Suliansyah, I., Anwar, A., & Yasin, S. (2021). Growth and Yield of Different Varieties of True Shallot Seed on Highland in West Sumatra, Indonesia. International Journal of Agronomy, 2021(1), 1-6. doi:https://doi-org.proxy.undip.ac.id/10.1155/2021/5563128

Badan Pusat Statistik. (2020). Kabupaten Demak dalam Angka. Demak: BPS Kabupaten Demak.

Badan Pusat Statistik. (2021). Kabupaten Demak dalam Angka. Demak: BPS Kabupaten Demak.

Badan Pusat Statistik. (2023). Kabupaten Demak dalam Angka. Demak: BPS Kabupaten Demak.

Badan Pusat Statistik. (2024). Kabupaten Demak dalam Angka. Demak: BPS Kabupaten Demak.

Badan Pusat Statistika. (2022). Kabupaten Demak dalam Angka. Demak: BPS Kabupaten Demak.

Bahadorzade, H., Saba, M. K., & Darvishi, H. (2022). Sun and convective mild air curing impact on Persian shallot quality changes and sprouting during postharvest storage. International Journal of Food Science & Technology, 57(7), 4638-4645. doi:https://doi.org/10.1111/ijfs.15803

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Bian, L., Cai, X. M., Luo, Z. X., Li, Z. Q., & Chen, Z. M. (2018). Decreased capture of natural enemies of pests in light traps with light-emitting diode technology. Annals of Applied Biology, 173(3), 251-260. doi:https://doi-org.proxy.undip.ac.id/10.1111/aab.12458

Budiman, I., Wagemakers, A., Derks, M., Sahara, & Moore, S. (2024). Socio-environmental systems in technology adoption in animal husbandry in South-East Asia: A framework synthesis approach. NJAS: Impact in Agricultural and Life Sciences, 96(1), 1-36. doi:https://doi.org/10.1080/27685241.2024.2349518

Chin, P. N. (2021). What Drives Excess Trading during the COVID-19 Pandemic? Asian Journal of Business and Accounting, 14(1), 113-143. doi:https://doi.org/10.22452/ajba.vol14no1.5

Damayanti, W. A., Raharjo, M., & Agushybana, F. (2021). enerimaan Konsep Green Hospital di Rumah Sakit Pemerintah (Studi Kasus RSUD Tugurejo Provinsi Jawa Tengah). Higeia Journal Of Public Health Research And Development, 5(2), 182-192. doi:https://doi.org/10.15294/higeia.v5i2.39818

de Beer, C. J., Boikanyo, S. N., & Venter, G. J. (2021). Evaluation of light emitting diode suction traps for the collection of livestock-associated Culicoides species in South Africa. Medical and Veterinary Entomology, 35(3), 408-416. doi:https://doi-org.proxy.undip.ac.id/10.1111/mve.12512

Elvina, E., & Wardhana, A. (2024). Strategi Peningkatan Kinerja Melalui Adopsi Media Sosial Pada Umkm Makanan Ringan. Journal of Business & Applied Management, 17(1), 55-68. doi:http://dx.doi.org/10.30813/jbam.v17i1.5149

Enriko, K. A., Kuswanda, K., Kurnianto, D., & Gustiyana, F. N. (2024). Implementation of LoRaWAN on Energy Monitoring System on the Onion Leaf Pest Light Trap device. Journal Of Telecommunication, Electronics, And Control Engineering (JTECE), 06(02), 109-116. doi:10.20895/JTECE.V6I2.1370

Feriadi, F., Sadono, D., & Purnaningsih, N. (2022). Analisis Keberlanjutan Usahatani Sawah Bukaan Baru di Kabupaten Bangka. Junal Penyuluhan, 19(1), 50-67. doi:https://doi.org/10.25015/19202343525

Firmansyah, Y. (2022). Pengaruh Alma Terhadap Kinerja Keuangan Dan Nilai Entitas Pada Bank Yang Terdaftar di BEI. Jurnal Sebi, 4(2), 22-31. doi:https://doi.org/10.37567/sebi.v4i2.1439

Foguesatto, C. R., Borges, J., & Machado, J. (2020). A review and some reflections on farmers' adoption of sustainable agricultural practices worldwide. Science of the Total Environment, 729. doi:https://doi.org/10.1016/j.scitotenv.2020.138831

Fornell, C., & Larcker, D. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research, 18(1), 39-50. doi:https://doi.org/10.1177/002224378101800104

Ghozali, I., & Latan, H. (2015). Partial Least Squares Konsep Teknik dan Aplikasi dengan Program Smart PLS 3.0. Semarang: Badan Penerbit Universitas Diponegoro.

Glover, D., Sumberg, J., & Andersson, J. (2016). The Adoption Problem; or Why We Still Understand So Little about Technological Change in African Agriculture. Outlook on Agriculture, 45(1), 3-6. doi:https://doi.org/10.5367/oa.2016.0235

Hair, J. F., Rhiser, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to Use and How to Report the Results of PLS-SEM. Emerald Publishing, 31(1), 2-24. doi:https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Ringle, C., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. Journal of Marketing Theory and Practice, 19(2), 139-152. doi:https://doi-org.proxy.undip.ac.id/10.2753/mtp1069-6679190202

Hartanto, Y. H. (2022). Analisis Pengaruh Penggunaan Media Terhadap Kinerja Usaha Mikro, Kecil, Dan Menengah (UMKM). Jurnal Ilmiah Manajemen Bisnis Dan Inovasi Universitas Sam Ratulangi (JMBI UNSRAT), 9(1), 323-334. doi:https://doi.org/10.35794/jmbi.v9i1.39254

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Herrera, S. I., Kallas, Z., Serebrennikov, D., Thorne, F., & McCarthy, S. (2023). Towards circular farming: factors affecting EU farmers' decision to adopt emission-reducing innovations. International Journal of Agricultural Sustainability, 21(3), 1-19. doi:https://doi.org/10.1080/14735903.2023.2270149

Hinojosa, V. A., Speelman, E., Thapa, A., Wei, H., McDonald, A., Tittonell, P., & Groot, J. (2018). Exploring farmer perceptions of agricultural innovations for maize-legume intensification in the mid-hills region of Nepal. International Journal of Agricultural Sustainability, 16(1), 74-93. doi:https://doi.org/10.1080/14735903.2018.1423723

Huffman, W. E. (2020). Human Capital and Adoption of Innovations: Policy Implications. Applied Economic Perspectives and Policy, 42(1), 92-99. doi:https://doi.org/10.1002/aepp.13010

Kaur, M., Singh, D., Anand, A., & Singh, T. (2023). Do attributes of happy seeder technology influence its adoption speed? An investigation using duration analysis in Northern India. International Journal of Agricultural Sustainability, 21(1), 1-17. doi:https://doi.org/10.1080/14735903.2023.2198324

Khairunnisa, N. F., Saidah, Z., Hapsari, H., & Wulandari, E. (2021). Peran Penyuluh Pertanian terhadap Tingkat Produksi Usahatani Jagung. Jurnal Penyuluhan, 17(2), 113-125. doi:https://doi.org/10.25015/17202133656

Khan, F. Z., Manzoor, S., Gul, H., Ali, M., Bashir, M., Akmal, M., . . . Joseph, S. (2021). Drivers of farmers' intention to adopt integrated pest management: a case study of vegetable farmers in Pakistan. Ecosphere, 12(10), 1-16. doi:https://doi-org.proxy.undip.ac.id/10.1002/ecs2.3812

Khawaja, M. J., & Alharbi, Z. N. (2021). Factors Influencing Investor Behavior: An Empirical Study Of Saudi Stock Market. International Journal of Social Economics, 48(4), 587–601. doi:https://doi.org/10.1108/IJSE-07-2020-0496

Khoza, T. M., Senyolo, G., Mmbengwa, V., & Soundy, P. (2019). Socio-economic factors influencing smallholder farmers' decision to participate in agro-processing industry in Gauteng province, South Africa. Cogent Social Sciences, 5(1), 1-14. doi:https://doi.org/10.1080/23311886.2019.1664193

Kirana, O. A., & Mulyana, M. (2022). aktor-Faktor Yang Mempengaruhi Minat Mahasiswa Ibi Kesatuan Untuk Berwirausaha Bidang Pariwisata. Bogor Hospitaly Journal, 6(2), 1-12. doi:https://doi.org/10.55882/bhj.v6i2.55

Lliwellyn, R. S., & Brown, B. (2020). Predicting Adoption of Innovations by Farmers: What is Different in Smallholder Agriculture? Applied Economic Perspectives and Policy, 42(1), 100-112. doi:https://doi.org/10.1002/aepp.13012

Lou, H., Liu, Z., & Xu, Q. (2022). Detection and elimination of shallot latent virus and onion yellow dwarf virus for potato onion (Allium cepa L. var. aggregatum Don). Annals of Applied Biology, 182(1), 112-120. doi:https://doi-org.proxy.undip.ac.id/10.1111/aab.12801

Michler, J. D., Tjernström, E., Verkaart, S., & Mausch, K. (2018). Money Matters: The Role of Yields and Profits in Agricultural Technology Adoption. American Journal of Agricultural Economics, 101(3), 710-731. doi:https://doi.org/10.1093/ajae/aay050

Mubyarto. (1992). Tanah dan Tenaga Kerja: (Kajian Sosial Ekonomi). Yogyakarta: Aditya Media.

Mwinuka, L., Mutabazi, K., Goreng, G., Sieber, S., Makindara, J., Kimaro, A., & Uckert, G. (2017). Simulated willingness of farmers to adopt fertilizer micro-dosing and rainwater harvesting technologies in semi-arid and sub-humid farming systems in Tanzania. Food Security, 9, 1237–1253. doi:DOI 10.1007/s12571-017-0691-1

Ngango, J., Nkurunziza, F., & Ndagijimana, J. (2022). Assessing rural farmers' willingness to pay for crop insurance scheme: Evidence from Rwanda. Cogent Economics & Finance, 10(1), 1-14. doi:https://doi.org/10.1080/23322039.2022.2104780

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Nugroho, Z. D., & Widiarti, P. W. (2021). Pengaruh Karakteristik Inovasi dan Saluran Komunikasi terhadap Keputusan Adopsi Inovasi Dompet Elektronik. Jurnal Ilmu komunikasi (LEKTUR), 4(4), 320-329. doi:http://dx.doi.org/10.21831/lektur.v4i4.18538

Nurmelia, N., & Lestari, H. S. (2022). Faktor – Faktor yang Mempengaruhi Perilaku Investor (Studi pada Investor Individu di Bursa Efek Indonesia). Jurnal Ilmiah Manajemen Bisnis Dan Inovasi Universitas Sam Ratulangi, 9(3), 1617-1638. doi:https://doi.org/10.35794/jmbi.v9i3.43153

Pangestuti, R., Sulistiyaningsih, E., Kurniasih, B., Murti, R. H., Harper, S., & Subandiyah, S. (2022). Phenological growth stage of tropical shallot (Allium cepa L. Aggregatum group) planted from seed in lowland area based on the BBCH scale. Annals of Applied Biology, 182(2), 257-266. doi:https://doi-org.proxy.undip.ac.id/10.1111/aab.12799

Prasetya, N. R., & Putro, S. (2019). Hubungan Tingkat Pendidikan dan Umur Petani Dengan Penurunan Jumlah Rumah Tangga Usaha Pertanian Sub Sektor Tanaman Pangan di Desa Meteseh Kecamatan Boja Kabupaten Kendal. Jurnal Edu Geography, 7(1), 47-56. doi:https://doi.org/10.15294/edugeo.v7i1.30134

Renu, I. R., & Christie, P. (2018). Does Gender Influence Investor Behavior in the Secondary Equity Market? International Journal of Applied Engineering Research, 8(11), 9651–9662.

Ringle, C. M., Sarstedt, M., & Straub, D. (2012). Editor's Comments: A Critical Look at the Use of PLS-SEM in "MIS Quarterly". Management Information Systems Quarterly, 36(1), 3-14. doi:https://doi.org/10.2307/41410402

Rogers, E. M. (1995). Lessons for Guidelines from the Diffusion of Innovations. The Joint Commission Journal on Quality Improvement, 21(7), 324-328. doi:https://doi.org/10.1016/S1070-3241(16)30155-9

Rogers, E. M. (2003). Diffusion of innovations. London: Routledge.

Roqayah, R., & Mala, O. (2018). Pendapatan Usahatani Bayam (Amaranthus sp) dan Kontribusi Terhadap Pendapatan Keluarga Petani di Kelurahan Lingkar Selatan Kecamatan Jambi Selatan Kota Jambi. Jurnal MeA (Media Agribisnis), 3(1), 30-38. doi:http://dx.doi.org/10.33087/mea.v3i1.32

Saputro, W. A., & Sariningsih, W. (2020). Kontribusi Pendapatan Usahatani Kakao terhadap Pendapatan Rumah Tangga Petani di Taman Teknologi Pertanian Nglanggeran Kecamatan Pathuk Kabupaten Gunungkidul. SEPA : Jurnal Sosial Ekonomi Pertanian dan Agribisnis, 16(2), 208-217. doi:http://dx.doi.org/10.20961/sepa.v16i2.35825

Sayyida, S. (2023). Structural Equation Modeling (Sem) Dengan Smartpls Dalam Menyelesaiakan Permasalahan Di Bidang Ekonomi. Journal MISSY (Management and Business Strategy), 4(1), 6-13. doi:https://doi.org/10.24929/missy.v4i1.2610

Setiawan, L. H., Khosyati, M. A., Nazira, N., Shara, S., Hidayati, B. W., & Suprehatin, S. (2022). Willingness Petani Menanam Bawang Putih: Bukti dari Kecamatan Sembalun, Nusa Tenggara Barat. Jurnal Penelitian Pertanian Terapan, 22(2), 111-122. doi:http://dx.doi.org/10.25181/jppt.v22i2.2419

Sholeh, M. S., Mublihatin, L., Laila, N., & Maimunah, S. (2021). Kontribusi Pendapatan Usaha Tani terhadap Ekonomi Rumah Tangga Petani di Daerah Pedesaan: Review. Jurnal Agromix, 12(1), 55-61. doi:http://dx.doi.org/10.35891/agx.v12i1.2330

Sihombing, Y., Mardiharini, M., Indrawanto, C., Warsito, W., Hermawan, H., Mulyono, J., & Purba, S. F. (2023). Analisis Efektivitas Diseminasi Inovasi Pertanian Komoditas Bawang Merah (Studi Kasus: Tiga Daerah Sentra Produksi Bawang Merah di Indonesia). Jurnal Agrikultura, 34(3), 346-357.

Suripto, S., & Anton, A. (2023). Analisis Pendapatan Petani Bawang Merah di Kabupaten Brebes. Journal of Business Economics and Agribusiness, 1(1), 1-12. doi:https://doi.org/10.47134/jbea.v1i1.47

ISSN 2580-0566; E-ISSN 2621-9778
http://ejournal2.undip.ac.id/index.php/agrisocionomics
Vol 9 (1): 125-147, March 2025

Syahidah, A. A., & Aransyah, M. F. (2023). Pengaruh E-Service Quality dan E-Trust terhadap ECustomer Loyalty pada Pengguna Dompet Digital DANA melalui E-Satisfaction sebagai Variabel Intervening. Jurnal SISFOKOM (Sistem Informasi dan Komputer), 12(1), 36-44.

Teye, J. K., Yaro, J., & Wiggins, S. (2024). Modernizing cocoa production in Ghana: successes, constraints, and future possibilities of innovation diffusion in the cocoa sector. African Geographical Review, 1-14. doi:https://doi.org/10.1080/19376812.2024.2357622

Tol, R., Rodriguez, C. M., Bruin, A. D., Yang, D., Taparia, T., & Griepink, F. C. (2022). Visual attraction of the European tarnished plant bug Lygus rugulipennis (Hemiptera: Miridae) to a water trap with LED light in chrysanthemum greenhouses and olfactory attraction to novel compounds in Y-tube tests. Pest Management Science, 78(6), 2523-2533. doi:https://doi-org.proxy.undip.ac.id/10.1002/ps.6881

Torgeson, K. F., Lagerkvist, C., Sok, J., Dicke, M., & Lansink, A. (2023). Cultivating choices: How social context shapes farmers' considerations in crop and soil health promoter selection. NJAS: Impact in Agricultural and Life Sciences, 95(1), 1-13. doi:https://doi.org/10.1080/27685241.2023.2256694

Triwidodo, H., & Tanjung, M. H. (2020). Hama Penyakit Utama Tanaman Bawang Merah (Allium ascalonicum) dan Tindakan Pengendalian di Brebes, Jawa Tengah. Agrovigor: Jurnal Agroekoteknologi, 13(2), 149-154.

Venter, G. J., Sebitsang, S. S., Swart, V. R., Boikanyo, S. N., & de Beer, C. J. (2021). Comparison of the efficiency of the Onderstepoort- and Centres for Disease Control ultraviolet light traps for the collection of livestock associated Culicoides species in South Africa. Medical and Veterinary Entomology, 36(1), 113-126. doi:10.1111/mve.12558

Yeshiwas, Y., Temsegen, Z., Wubie, M., & Wagnew, T. (2023). Effects of Varieties and Different Environments on Growth and Yield Performance of Shallot (Allium cepa var. aggregatum). International Journal of Agronomy, 2023(1), 1-12. doi:https://doi-org.proxy.undip.ac.id/10.1155/2023/3276547