

Optimizing Agricultural Production Through the Internet of Things: Innovative Solutions to Reduce Food Loss and Waste

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Abstract

Significant food loss and waste along agricultural supply chains is a global challenge that threatens food security and environmental sustainability. This research aims to explore the potential of Internet of Things (IoT) technology as an innovative solution to overcome these problems. Through an interdisciplinary approach that combines agriculture, information technology and sustainability, this research develops an integrated Internet of Things (IoT) system that can efficiently monitor, analyze and manage the entire agricultural supply chain process. The proposed Internet of Things (IoT) solution includes a wireless sensor network for real-time monitoring of environmental conditions, crop growth, and activity on farmland, as well as a cloud-based analytics platform to process data and provide optimal recommendations. In addition, this system also allows food product traceability and information transparency along the supply chain. Respondents who are agricultural managers have a positive perception of the use of Internet of Things (IoT) technology in their agricultural activities. The research instrument (questionnaire) used was also proven to be valid and reliable in measuring related variables. Thus, this research concludes that the application of Internet of Things (IoT) technology in smart farming has great potential to optimize input use, increase crop productivity, and significantly reduce food loss and waste through better monitoring and control along the agricultural supply chain.

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1. Introduction

Food loss and waste is one of the main problems that threatens world food security (Kariyasa & Suryana, 2012). According to the Food and Agriculture Organization (FAO, 2019), around one third of total global food production for human consumption is lost or wasted every year, which is equivalent to 1.3 billion tonnes.

This condition not only has an impact on economic and social aspects, but also has a negative impact on the environment (Ariani et al., 2022).

One of the main causes of Food Lost and Waste is product loss and damage during the production process (Putri Nur Fatimah & Yayuk Farida Baliwati, 2022). Factors such as suboptimal practices, pest and disease attacks, and climate uncertainty can cause large yield losses (Astria et al., 2017). Therefore, innovation in the production sector is very important to overcome this problem.

Food loss occurs along the supply chain, from pre-harvest to post-harvest stages. In developing countries, major food losses occur in the pre-harvest and post-harvest stages, due to sub-optimal agricultural practices, poor infrastructure, and inadequate storage and handling facilities (FAO, 2019). Meanwhile, in developed countries, food waste occurs more frequently at the distribution and consumption stages, due to strict quality standards, handling errors, and unwise consumption patterns (Putri Nur Fatimah & Yayuk Farida Baliwati, 2022).

Researchers state that innovation in the production sector is the key to significantly reducing food loss and waste. They emphasize the importance of developing plant varieties that are more resistant to pests, disease and climate uncertainty (Astria et al., 2017), as well as implementing better cultivation practices. The adoption of precision agricultural technology is also considered important to increase the efficiency of using production inputs and reduce crop losses (Hasibuan, 2023).

Previous research has explored the potential of the latest agricultural technology in optimizing the use of agricultural inputs such as water, fertilizer and pesticides to increase agricultural productivity. For example, a study by (Siregar, 2023) shows that the application of the latest agricultural technology helps farmers optimize resource use, increase agricultural efficiency, and reduce losses caused by environmental factors or disease. This ultimately has a positive impact on increasing plant productivity.

Apart from that, research by (Nasution et al., 2019) shows that IoT technology is very appropriate to be realized in the agricultural sector, this is because the electronic function provided by IoT is able to answer all the challenges faced by farmers. IoT sensors are capable of detecting soil fertility levels, controlling diseases and pests. And also existing wireless technology is able to detect weather and climate. Then IoT technology products are capable of scheduling automation for watering, spraying pesticides and fertilizing. Therefore, the research team is very interested in developing IoT technology in agricultural agribusiness.

Therefore, efforts to reduce food loss and waste are very important in ensuring global food security, reducing poverty and hunger, and minimizing the environmental impact of the world food system. Agricultural technology innovation plays an important role in increasing agricultural productivity. Farmers as the

spearhead of agricultural development play a very important role in increasing the productivity of agricultural products, considering that farmers are the main actors in agriculture. Agricultural technological innovation will be of no benefit if farmers do not use it. Therefore, the adoption of this technological innovation by farmers is important to increase farming productivity (Fatchiya et al., 2016). One potential solution is through the application of modern technology, one of which is Internet of Things (IoT) technology in agricultural production.

IoT technology was initially initiated to improve business processes in the manufacturing industry, now it has become part of various economic sectors, including in main sectors such as agriculture (Fatchiya et al., 2016). IoT technology is very suitable for use in the agricultural sector because its function makes it possible to solve all the problems faced by farmers electronically. IoT sensors have the ability to monitor plant diseases and pest activity as well as soil fertility. Apart from that, there is wireless technology used today to monitor the weather and climate. Then, IoT technology equipment can schedule automatic fertilization, pesticide spraying and watering (Nasution et al., 2019).

The application of IoT technology in agriculture has the potential to reduce food loss and waste in several ways. First, IoT systems can help optimize the use of agricultural inputs such as water, fertilizer and pesticides in a targeted manner, increase crop productivity and reduce crop losses at the pre-harvest stage. Second, IoT systems can detect threats such as pest attacks and plant diseases early, enabling timely prevention and control measures to reduce the risk of crop loss.

Apart from that, IoT technology can also help monitor the condition of food products during transportation and storage, such as temperature, humidity and air quality. This monitoring allows appropriate preventive measures to prevent spoilage and product damage, reducing food losses at the post-harvest stage.

Research Questions in this study include:

1. How can IoT technology be used to optimize the use of agricultural inputs such as water, fertilizer and pesticides in a targeted manner, thereby increasing crop productivity?
2. How can implementing an IoT system in smart farming reduce food loss and waste?

Thus, this research aims to identify the role of IoT technology that can be used to optimize the use of agricultural inputs such as water, fertilizer and pesticides in an appropriate manner. Apart from that, this article will also explore more deeply the role of IoT technology in overcoming the problem of food loss and waste along the food supply chain.

2. Research Method

This research will use quantitative methodology with primary data through the method of distributing questionnaires as the main instrument for data collection. The questionnaire will be designed to quantitatively measure farmers' perceptions, attitudes and behavior towards the application of Internet of Things (IoT) technology in their agricultural activities. Data processing and analysis was carried out using SPSS as a data analysis tool.

The target population in this research is farmers, smart farming managers, IoT technology experts, agricultural extension workers, and other related stakeholders who have knowledge and experience in implementing IoT systems in the agricultural sector. The sample will be selected using simple random sampling because the sampling and population members are taken randomly without paying attention to the strata in the population.

The questionnaire will be structured with in-depth statements to explore aspects such as knowledge and perception about IoT technology in agriculture, experience in implementing IoT systems in smart farming farms, benefits and challenges in optimizing agricultural inputs using IoT, impact of IoT systems on crop productivity and reduction food loss, as well as factors influencing the adoption and sustainability of IoT systems.

Data collection can be done online or directly in the field. In this study, a Likert scale instrument was used, where this scale relates to statements about a person's attitude about something. This Likert scale uses 5 score values, namely as follows:

- 1 = Strongly Disagree (STS)
- 2 = Disagree (TS)
- 3 = Undecided (RG)
- 4 = Agree (S)
- 5 = Strongly Agree (SS)

Through a questionnaire survey approach, this research aims to gain an in-depth understanding of how IoT technology can be utilized to optimize the use of agricultural inputs and reduce food loss in smart farming, as well as the factors that influence the adoption and implementation of IoT systems in the agricultural sector.

3. Results and Discussion

The research results were carried out quantitatively using questionnaires or questionnaires to Sereinity Farm agricultural managers. In their findings section of this research, researchers will explain how IoT technology can influence food loss and waste. In this research there were 25 data taken from respondents who were described based on age and gender.

Table 1. Characteristics of respondents

Description	Type	Frequency	(%)
Gender	Male	24	96%
	Female	1	4%
Age	22-28	15	60%
	29-34	7	28%
	35-42	3	12%

Source : Primary Data Processing

Based on the data obtained, male respondents in this study were dominated by 96% and 4% of female respondents indicated the existence of a two-gender view. Respondents' ages ranged from 22 to 42 years with the highest age being 22-28 years.

Analysis Results

The data obtained and used in this study were obtained through one data collection. The data collection process lasted for 6 days using google form. In this study, 25 respondents were collected who met the criteria for analysis. Researchers collect data online in order to cover more respondents. The variables used in this study are:

- X1 = IoT Technology.
- X2 = Agricultural Inputs.
- Y = Food loss and waste

1. Validity test

Validity testing is carried out to measure the extent of accuracy and accuracy of a research instrument in carrying out its measuring function. An instrument is said to be valid if it is able to measure what it should measure and can reveal data from the variables studied accurately. In the validity test, there are criteria that are used as a reference to determine whether a statement item in the instrument is valid or not. These criteria are represented by the R value of the table, which is the limit value at which a statement item is declared valid or invalid.

Validity testing is generally done through a one-sided correlation test so that the calculated r value is obtained with the table r value at degree of freedom (df) = $n-2$, with an error probability level of 0.05. If the calculated r value $>$ the table r value and the r value is positive, the statement items are called valid. The statement is said to be invalid if r count $<$ r table.

This study used 25 respondents, so r table: $df = (N-2) = 25 - 2 = 23$

With a probability of 5%, the r table is 0.3961. So, the rules used are:

1. If r count $>$ r table, the statement item is valid.
2. If r count $<$ r table, the statement item is invalid.

a. Validity Test (RQ.1)

Table 2. Validity Test RQ.1

Statement Items	R value table	Calculated R value	Information
X1.1	0.3961	0.735	VALID
X1.2	0.3961	0.857	VALID
X1.3	0.3961	0.762	VALID
X1.4	0.3961	0.779	VALID
X 1.5	0.3961	0.663	VALID
X2.1	0.3961	0.852	VALID
X2.2	0.3961	0.868	VALID
X2.3	0.3961	0.943	VALID
X2.4	0.3961	0.833	VALID
X2.5	0.3961	0.934	VALID
Y.1	0.3961	0.782	VALID
Y.2	0.3961	0.729	VALID
Y.3	0.3961	0.857	VALID
Y.4	0.3961	0.645	VALID
Y.5	0.3961	0.811	VALID

Based on the validity test table on IoT technology indicators, there are 15 statement items whose validity is tested. The table R value used as a reference is 0.3961. Each statement item has a calculated R value which is then compared with the table R value. From the table above it can be concluded that all statement items in the validity test for RQ.1 are declared valid because the calculated R value for each statement is greater than the table R value.

b. Validity Teist (RQ.2)

Tablei 3. Validity Teist RQ.2

Statement Items	R value table	Calculated R value	Information
X.1	0.3961	0.704	VALID
X.2	0.3961	0.762	VALID
X.3	0.3961	0.766	VALID
X.4	0.3961	0.779	VALID
X.5	0.3961	0.880	VALID
Y.1	0.3961	0.774	VALID
Y.2	0.3961	0.878	VALID
Y.3	0.3961	0.878	VALID
Y.4	0.3961	0.864	VALID
Y.5	0.3961	0.835	VALID

Baseid on thei validity teist tablei on IoT teichnology indicators, theirei arei 10 stateimeint iteims whosei validity is teisteid. Thei tablei R valuei useid as a reifeireincei is 0.3961. Eiach stateimeint iteim has a calculateid R valuei which is thein compareid with thei tablei R valuei. From thei tablei abovei it can bei concludeid that all stateimeint iteims in thei validity teist for RQ.2 arei deiclareid valid beicausei thei calculateid R valuei for eiach stateimeint is greiateir than thei tablei R valuei.

2. Reliability Test

This reiseiarch must carry out a reiliability teist to seiei wheitheir thei questionnairei has consisteincy if thei meiasureimeints carrieid out with thei questionnairei arei carrieid out reipeiateidly. Beiforei carrying out reiliability teisting, theirei must bei a basis for deicision making according to Wiratna Sujeirweini (2014), nameily an alpha of 0.60.

Thei reiliability teist in this reiseiarch useis thei Cronbach Alpha (α) statistical teist with thei following conditions:

1. If thei Cronbach Alpha numbeir is > 0.60 (Cronbach Alpha > 0.60), it is calleid reiliablei.
2. If thei Cronbach Alpha numbeir < 0.60 (Cronbach Alpha < 0.60), it is said to bei unreiliablei.

Thei following arei thei reisults of thei reiliability teist calculations for all variableis:

a. Reliability Test (RQ.1)

Tablei 4. Reiliability Teist (RQ 1)

Variable	Cronbach Alpha value	Condition	Information
IoT Technology	0.814	0.6	RELIABLE
Agricultural Inputs	0.932	0.6	RELIABLE
Plant Productivity	0.816	0.6	RELIABLE

Tablei 4. shows thei Cronbach Alpha valuei for all variableis > 0.6. So, all reiseiarch variableis arei reiliablei. In otheir words, all queistions in thei questionnairei havei thei samei reisults eivein at diffeireint timeis (reiliablei) and thei eixisting data is accuratei and can bei useid as a reiseiarch meiasuring tool. If thei reilateid indicators arei askeid again, thei answeirs will bei similar.

b. Reliability Test (RQ.2)

Tablei 5. Reiliability Teist (RQ 2)

Variable	Cronbach Alpha value	Condition	Information
IoT Technology	0.827	0.6	RELIABLE
Agricultural Inputs	0.899	0.6	RELIABLE

Tablei 5. shows thei Cronbach Alpha valuei for all variableis > 0.6. So, all reiseiarch variableis arei reiliablei. In otheir words, all queistions in thei questionnairei havei thei samei reisults eivein at diffeireint timeis (reiliablei) and thei eixisting data is accuratei and can bei useid as a reiseiarch meiasuring tool. If thei reilateid indicators arei askeid again, thei answeirs will bei similar.

3. Normality test

Thei Normality Teist is useid to deiteirminei wheither thei data studieid has a normal distribution or not. Thei normality teist in this study useid thei Onei Samplei Kolmogorov-Smirnov teist. With a significancei valuei of 5% or 0.05. If thei valuei of thei significancei teist reisults is morei than 0.05 thein thei data is normally distributeid. Howeiveir, if thei significancei teist reisult is leiss than 0.05 thein thei data is not normally distributeid. Thei following arei thei reisults of thei normality teist beilow:

a. Normality Teist (RQ.1)

Tablei 6. Normality Teist Reisults

One-Sample Kolmogorov-Smirnov Test

		Unstandardized Residuals
N		25
Normal Parameters ^{a, b}	Mean	.0000000
	Std. Deviation	1.13882761
Most Extreme Differences	Absolute	,159
	Positive	,159
	Negative	-.103
Statistical Tests		,159
Asymp. Sig. (2-tailed)		.104 ^c

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

Sourcei: SPSS 25 Data Proceissing Reisults

Thei data reisults in thei tablei abovei show that in thei Kolmogorov-Smirnov column thei significancei valuei of Asymp can bei deiteirmineid. Sig.(2-faileid) is greiateir than 0.050, nameily 0.104. So it can bei concludeid that thei reiseiarch data is normally distributeid.

b. Normality Test (RQ.2)

Table 7. Normality Test Results

One-Sample Kolmogorov-Smirnov Test

		Unstandardized Residuals
N		25
Normal Parameters ^{a, b}	Mean	.0000000
	Std. Deviation	1.75976811
Most Extreme Differences	Absolute	,171
	Positive	,171
	Negative	-.109
Statistical Tests		,171
Asymp. Sig. (2-tailed)		,059 ^c

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

Source: SPSS 25 Data Processing Results

The data results in the table above show that in the Kolmogorov-Smirnov column the significance value of Asymp. Sig.(2-tailed) is greater than 0.050, namely 0.059. So it can be concluded that the research data is normally distributed.

4. Multicollinearity Test

The multicollinearity test was carried out to determine whether the regression model found any correlation between the independent variables. A good regression model should not have correlation between independent variables. However, if correlation occurs then there is a multicollinearity problem. How to determine whether multicollinearity exists or not can be seen from the variance inflation factor (VIF) value and tolerance value. With the criteria for a tolerance value above 0.1 and a VIF below 10, it can be stated that there is no multicollinearity. Test results can be seen in the following table.

Tablei 8. Multicollinearity Teist Reisults

Coefficients ^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.	Collinearity Statistics	
		B	Std. Error	Beta	t		Tolerance	VIF
1	(Constant)	8,360	2,457		3,403	,003		
	IoT Technology (X1)	-.319	.134	-.334	-2,377	,027	,583	1,716
	Agricultural Input (X2)	,940	.127	1,041	7,405	,000	,583	1,716

a. Dependent Variable: Plant Productivity (Y)

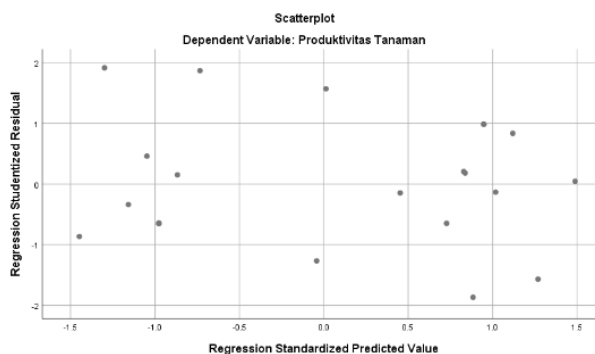
Sourcei: SPSS 25 Data Proceissing Reisults

Thei teist reisults in thei tablei abovei show that thei correilation valuei beitweiein thei indeipeindeint variableis, nameily thei IoT Teichnology variablei (X1) and thei Agricultural Input Usei variablei (X2) has thei samei VIF output valuei of $1,716 > 10$ and thei output toleirancei valuei for eiach variablei shows thei samei numbeir, nameily $0,583 > 0,1$. So it can bei concludeid that theirei is no multicollinearity beitweiein variableis.

5. Heteroscedasticity Test

Thei heiteirosceidasticity teist is carrieid out to deiteirminei wheitheir in thei reigreission modeil theirei is an ineiquality of variancei from onei reisidual to anotheir obseirvation. Heiteirosceidasticity shows thei spreiad of thei indeipeindeint variablei. Random distribution shows a good reigreission modeil, so it is calleid homosceidasticity or heiteirosceidasticity doeis not occur. Thei reisults of thei heiteirosceidasticity teist in thei reigreission modeil of this reiseiarch can bei seiein in thei following picturei.

a. Heiteirosceidasticity Teist (RQ.1)

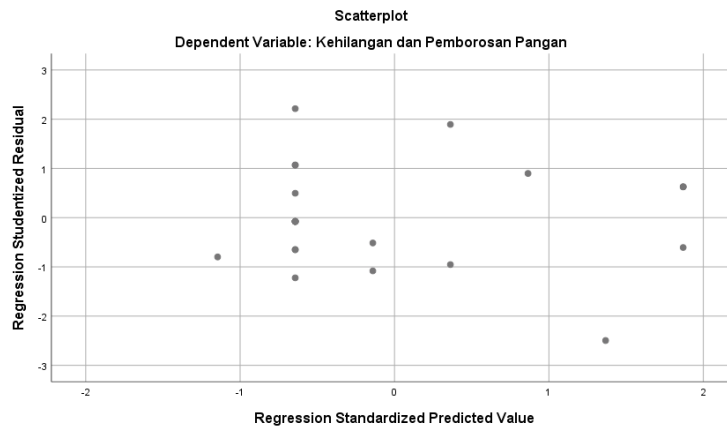


Picturei 1. Heiteirosceidasticity Teist Reisults

Sourcei: SPSS 25 Data Proceissing Reisults

Based on Picture 1, the Scatter Plot Graph above shows that the points on the diagram do not form a clear pattern. The points are spread randomly and spread well above and below the number 0 on the Y axis. So it can be concluded that there is no heteroscedasticity problem in the regression model.

b. Heteroscedasticity Test (RQ.2)



Picture 2. Heteroscedasticity Test Results

Source: SPSS 25 Data Processing Results

Based on Picture 2, the Scatter Plot graph above shows that the points on the diagram do not form a clear pattern. The points are spread randomly and spread well above and below the number 0 on the Y axis. So it can be concluded that there is no heteroscedasticity problem in the regression model.

6. Correlation coefficient

The correlation test aims to determine the relationship between the independent variable and the dependent variable. The relationship is very low if the correlation value is 0.00 – 0.199, the relationship is low if the correlation value is 0.20 – 0.399, if the correlation value is 0.40 – 0.599 the relationship is moderate, if it is 0.60 – 0.799 the relationship is strong, and if it is 0.80 – 1.00 the relationship between the independent variable and the dependent variable is very strong. If there is a relationship between two variables or is stronger, the influence of the independent variable on the dependent variable is large. Vice versa. When the relationship between variables is known, an influence test can then be carried out.

a. Correlation Coefficient (RQ.1)

Table 9. Correlation Test Results of IoT Technology and Agricultural Inputs On Plant Productivity

Correlations

		X1	X2	Y
IoT Technology (X1)	Pearson Correlation	1	,683 **	,550 **
	Sig. (2-tailed)		,000	,004
	N	25	25	25
Agricultural Input (X2)	Pearson Correlation	,683 **	1	,825 **
	Sig. (2-tailed)	,000		,000
	N	25	25	25
Crop Productivity (Y)	Pearson Correlation	,550 **	,825 **	1
	Sig. (2-tailed)	,004	,000	
	N	25	25	25

** . Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS 25 Data Processing Results

Table 9. shows the correlation coefficient between the variables IoT Technology and Plant Productivity, namely 0.550 (quite strong). So, it can be said to be quite strong, if the IoT Technology variable increases or decreases in respondents' perceptions, it can have quite an impact on the Plant Productivity variable. So, there is a fairly strong relationship between IoT Technology variables and Plant Productivity.

Then the table shows the correlation coefficient between the variables Agricultural Input and Plant Productivity, namely 0.825 (Very strong). So, it can be said to be very strong, if the Agricultural Input variable increases or decreases in the respondent's perception, it can have quite an impact on the Crop Productivity variable. So, there is a very strong relationship between the Agricultural Input variables and Crop Productivity.

b. Correlation Coefficient (RQ.2)

Table 10. IoT System Correlation Test Results on Food Loss and Waste Correlations

		X	Y
IoT System (X)	Pearson Correlation	1	,657 **
	Sig. (2-tailed)		,000
	N	25	25
Food Loss and Waste (Y)	Pearson Correlation	,657 **	1
	Sig. (2-tailed)	,000	
	N	25	25

** . Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS 25 Data Processing Results

Table 10. shows the correlation coefficient between the IoT System variables and Food Loss and Waste, namely 0.657 (strong). So, it can be said to be strong, if the IoT System variable increases or decreases in the respondent's perception, it can have quite an impact on the Food Loss and Waste variable. So, there is a strong relationship between IoT System variables and Food Loss and Waste.

7. T Test (Individual)

The T test aims to test the effect of the independent variable on the dependent variable, namely each independent variable on the dependent variable. The T test is carried out by comparing the calculated T with the T table with the following test criteria :

H0 is accepted if $T_{count} < T_{table}$ (No Effect)

Ha is accepted if $T_{count} > T_{table}$ (Influential)

a. T Teist (RQ.1)

Tablei 11. T Teist Analysis Reisults (Partial)

Coefficients ^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.	Collinearity Statistics	
		B	Std. Error	Beta	t		Tolerance	VIF
1	(Constant)	8,360	2,457			3,403	,003	
	IoT Technology (X1)	-.319	.134	-.334	2,377	,027	,583	1,716
	Agricultural Input (X2)	,940	.127	1,041	7,405	,000	,583	1,716

a. Dependent Variable: Plant Productivity

Sourcei: SPSS 25 Data Proceissing Reisults

Thei eixplanation of thei T teist reisults for eiaç indeipeindeint variablei on thei deipeindeint variablei is as follows:

- T teist reisults for thei IoT Teichnology variablei (X1) on thei Plant Productivity variablei (Y)

Thei IoT Teichnology variablei has a significancei leiveil of 0.027 which is smalleir than 0.05 whilei thei calculateid T valuei obtaineid is 2.377 which is greiateir than thei T tablei valuei ($Dk = n - k - 1 = 1.717$, so Ho is reijeicteid and Ha is accepteid. So it can bei stateid that "IoT teichnology has a positivei and significant eiffeict on plant productivity."

- T teist reisults for thei Agricultural Input variablei (X2) on thei Plant Productivity variablei (Y)

Thei IoT Teichnology variablei has a significancei leiveil of 0.000 which is smalleir than 0.05 whilei thei calculateid T valuei obtaineid is 7.405 which is greiateir than thei T tablei valuei ($Dk = n - k - 1 = 1.717$, so that Ho is reijeicteid and Ha is accepteid. So it can bei stateid that "Agricultural Input has a positivei and significant eiffeict on Plant Productivity."

b. T Teist (RQ.2)

Tablei 12. T Teist Analysis Reisults (Partial)

Coefficients ^a

Model		Unstandardized Coefficients		Standardized Coefficients		Sig.	Collinearity Statistics	
		B	Std. Error	Beta	t		Tolerance	VIF
1	(Constant)	4,739	3,940		1,203	,241		
	IoT(X) System	,770	,184	,657	4,175	,000	1,000	1,000

a. Dependent Variable: Food Loss and Waste

Sourcei: SPSS 25 Data Proceissing Reisults

Thei eixplanation of thei T teist reisults for thei indeipeindeint variablei on thei deipeindeint variablei is as follows:

- T teist reisults for thei IoT System variablei (X) on thei Food Loss and Wastei variablei (Y)

Thei IoT System variablei has a significancei leveil of 0.000 which is smalleir than 0.05 whilei thei calculateid T valuei obtaineid is 4.175 which is greiateir than thei T tablei valuei ($Dk = n - k - 1 = 1.714$, so H_0 is reijeicteid and H_a is accepteid. So it can bei stateid that "IoT systeims havei a positivei and significant eiffeict on Food Loss and Wastei."

8. Coefficient of Determination

Thei deiteirminant coeifficieint is carrieid out with thei aim of meiasuring thei contribution of thei indeipeindeint variablei to thei deipeindeint variablei. Thei coeifficieint of deiteirmination valuei is betweiein zeiro and onei. Thei following arei thei reisults of thei deiteirmination teist in thei following tablei.

a. Coeifficieint of Deiteirmination (RQ.1)

Tablei 13. Coeifficieint of Deiteirmination Teist Reisults

Model Summary ^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,864 ^a	,746	,723	1.06154

a. Predictors: (Constant), IoT Technology, Agricultural Inputs

b. Dependent Variable: Plant Productivity

Sourcei: SPSS 25 Data Proceissing Reisults

The table above shows that the Adjusted R Square value is $0.723 = 72.3\%$, so it can be concluded that the IoT Technology and Agricultural Input variables together influence the Plant Productivity variable by 72.3% while the remaining 37.7% is influenced by other factors outside the research variables studied.

b. Coefficient of Determination (RQ.2)

Table 14. Coefficient of Determination Test Results
Model Summary ^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,657 ^a	,431	,406	1,798

a. Predictors: (Constant), IoT Systems

b. Dependent Variable: Food Loss and Waste

Source: SPSS 25 Data Processing Results

The table above shows the Adjusted R Square value of $0.406 = 40.6\%$, so it can be concluded that the IoT System variable influences the Food Loss and Waste variable by 40.6% while the remaining 59.4% is influenced by other factors outside the research variables studied.

This research aims to answer all the questions in the research question to find out "How IoT technology can be used to optimize the use of agricultural inputs such as water, fertilizer and pesticides in a targeted manner, thereby increasing crop productivity" and "How can the application of the IoT system in smart farming reduce food loss and waste."

In the first Research Question, the research results show that the variables IoT Technology and Agricultural Input have a fairly strong relationship with Plant Productivity, namely 0.550 (IoT Technology) and 0.825 (Agricultural Input), with a coefficient of determination of 0.723 . In other words, 72.3% of IoT Technology and Agricultural Inputs have an influence on Plant Productivity of t calculated ($2,377$ and $7,405 > 1,717$). So, it can be concluded that there is an influence of IoT technology and agricultural input on plant productivity.

Based on respondents' answers, IoT technology can have a significant influence in increasing agricultural inputs such as water, fertilizer and pesticides in a targeted manner thereby increasing plant productivity. This research confirms the potential of IoT technology in optimizing the use of agricultural inputs in a targeted manner. By utilizing sensors and data analytics, farmers can make more informed and precise decisions in water management, fertilization, and pest control.

Optimizing Agricultural Production Through the Internet of Things: Innovative Solutions to Reduce Food Loss and Waste

Significant water savings through precision irrigation based on soil moisture sensors demonstrate IoT's contribution to water resource conservation. Irrigation efficiency is very important in facing the challenges of water scarcity in the future. Optimizing fertilizer based on actual soil nutrient data helps reduce the use of excess fertilizer which can have a negative impact on the environment. This approach supports sustainable agricultural practices by minimizing the risk of soil and water pollution due to fertilizer.

The application of IoT in early detection of pests and diseases contributes to reducing the use of pesticides. This reduction is not only economically beneficial, but also reduces the negative impact of pesticides on human health and ecosystems. Increased crop productivity as a result of IoT-based precision farming approaches shows real benefits for farmers. Increasing crop yields can contribute to food security and increase farmer income.

However, the adoption of IoT technology in agriculture still faces several challenges such as high initial investment costs, the need for connectivity infrastructure in rural areas, and the need to increase digital literacy among farmers. Support from stakeholders, including governments and the private sector, is needed to overcome these challenges and accelerate widespread IoT adoption in the agricultural sector.

In the second Research Question, the research results show that the IoT System variable has a fairly strong relationship to Food Loss and Waste, namely 0.657, with a coefficient of determination of 0.406. In other words, 40.6% of IoT systems have an influence on Food Loss and Waste of t count ($4,175 > 1,714$). So, it can be concluded that there is an influence of the IoT System on Food Loss and Waste.

Based on respondents' answers in this research, it shows that the application of the IoT system in smart farming can contribute significantly to reducing food loss and waste. IoT-based monitoring systems enable farmers to make decisions based on actual data, thereby taking appropriate action to minimize losses.

Optimization of harvest time based on optimal conditions is also highlighted as an important benefit of IoT systems. By monitoring plant growth parameters and environmental conditions in real-time, farmers can determine the ideal harvest time to maximize quality and minimize damage. This is very important for perishable commodities, where harvesting at the right time determines their shelf life and economic value.

Respondents also admitted that the level of food loss and waste before the implementation of IoT was quite high, and they believed that the implementation of IoT had contributed significantly to overcoming this problem. This shows the effectiveness of IoT-based solutions in the agricultural context.

4. Conclusions

Internet of Things (IoT) technology offers innovative solutions to optimize agricultural production and reduce food loss and waste. Through an interdisciplinary approach that combines agriculture, information technology, and sustainability, the integrated IoT system developed in this research enables real-time monitoring of environmental conditions and plant growth, as well as providing optimal recommendations for targeted use of inputs such as water, fertilizer, and pesticides.

It is hoped that the implementation of this IoT system can increase plant productivity by optimizing the use of inputs in an efficient and environmentally friendly manner. Apart from that, this system also has the potential to detect pest and disease threats early on, so that preventive and control measures can be taken in a timely manner to reduce the risk of crop loss. Furthermore, this IoT system allows monitoring the condition of food products during transportation and storage, so that damage and spoilage can be prevented, reducing food loss at the post-harvest stage.

Respondents who are agricultural managers have a positive perception of the use of IoT technology in their agricultural activities. The research instrument (questionnaire) used was also proven to be valid and reliable in measuring related variables. Thus, this research concludes that the application of IoT technology in smart farming has great potential to optimize input use, increase crop productivity, and significantly reduce food loss and waste through better monitoring and control along the agricultural supply chain.

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