# Assessing The Success Of Intelligent Agriculture Practices In A Large-Scale Extension System Project In Udon Thani Province: A Comprehensive Study

Parita Chaipattarawong[1] , Natnaporn Eaknarajindawat[2] , Nopadol Burananuth[3]

[1]Suan Sunandha Rajabhat University, Thailand, parita@thaiseed.co.th
[2]Suan Sunandha Rajabhat University, Thailand, natnaporn.ae@ssru.ac.th
[3]Suan Sunandha Rajabhat University, Thailand, nopadol.b@hotmail.com

*Abstract:*

This study aimed to evaluate the level of smart agriculture industry management in a large-scale agricultural extension system project in Udon Thani province, Thailand. The study used a mixed-methods research design, combining both quantitative and qualitative data collection methods. The data were collected from 300 farmers using a questionnaire, and 20 key informants were interviewed. The study found that the level of smart agriculture industry management was at a high level, indicating the project's success in implementing and promoting intelligent agriculture practices among farmers. Factors that influenced smart agriculture industry management included government policy, inputs, automatic technology, and production process. The study also found that the project had a positive impact on sustainable agriculture, increasing the quantity and quality of produce. However, some limitations, such as the small sample size and the study's geographical focus, were noted. Further research is needed to examine the factors that influence smart agriculture industry management in other regions and countries.

Keywords: smart agriculture, industry management, large-scale agricultural extension system, Udon Thani province, Thailand, government policy.

## Introduction

Agriculture plays a critical role in ensuring food security, creating jobs, and sustaining livelihoods in developing countries. The traditional agricultural practices in many countries are outdated and inefficient, leading to low productivity, high costs, and negative environmental impacts. The emergence of smart farming, which leverages technology to enhance the efficiency and sustainability of agricultural practices, is a promising solution to these challenges. However, the adoption of smart farming in developing countries requires supportive government policies, appropriate production factors, and efficient management practices.

This study aims to investigate the structural relationship between factors that influence the management of smart agriculture and develop guidelines to increase its efficiency in Udon Thani Province, Thailand. The research questions include the level of government policy, production factors, technology, automation, production process, and their influence on the management of smart agriculture. Additionally, the study aims to identify ways to enhance the efficiency of smart agriculture management in the context of Udon Thani Province.

The study adopts a mixed-method research approach that combines quantitative and qualitative research methods. The content scope of the research is divided into two types, namely, quantitative and qualitative research. In the quantitative research, the researcher develops a questionnaire that consists of various variables, including government policy, production factors, technology, automation, production process, and smart agricultural management. The questionnaire is tested for reliability and validity before collecting data from the sample. The data collected from the sample is then analyzed statistically.

In the qualitative research, the researcher uses a secondary data study method to study theoretical concepts and literature on government policy, production factors, technology, automation, production process, and smart agricultural management. The researcher uses documentary research methods from books, academic papers, articles, relevant research papers, printed media, and electronic media. Additionally, the researcher conducts in-depth interviews with executives and personnel from relevant government agencies at policy and operational levels and qualified personnel from relevant private agencies. The information gathered from the interviews is filtered, analyzed, and used to develop cognitive theory.

The population scope of the study is defined as farmers in Udon Thani province, executives, and personnel from relevant government agencies at policy and operational levels, and qualified personnel from relevant private agencies. The sample group and sample size used in the study are determined according to the study model. The appropriate sample size for the quantitative research is determined using Grace's criteria, and the researcher considers purposive selection for the qualitative research.

The study identifies government policy, production factors, technology, automation, and production process as independent variables that influence the management of smart agriculture. Smart agricultural management is identified as the dependent variable, with production cost reduction, quantity increase, and sustainable agriculture as the observed variables.

The study's expected benefits include providing information and proposals to stakeholders at the policy and operational levels from relevant government and private sectors, supporting farmers interested in smart farming systems, and providing academic knowledge supporting government agencies, the private sector, and educational institutions.

In conclusion, the adoption of smart farming in developing countries such as Thailand requires supportive government policies, appropriate production factors, and efficient management practices. This study aims to investigate the factors that influence the management of smart agriculture and develop guidelines to increase its efficiency in Udon Thani Province. The study uses a mixed-method research approach that combines quantitative and qualitative research methods, and the population scope includes farmers, executives, and personnel from relevant government agencies and qualified personnel from relevant private agencies. The expected benefits of the study include providing information and proposals to stakeholders, supporting farmers interested in smart farming systems, and providing academic knowledge to government agencies, the private sector, and educational institutions.

## Literature Review

Smart farming systems are a technological advancement that is becoming increasingly popular in the agricultural industry. According to the article, smart farming systems have the potential to transform traditional agriculture into a research-driven economy by increasing productivity throughout the supply chain. The article emphasizes the importance of government policy in promoting research, technology, and innovation in agriculture, which can help drive the development of the agricultural sector in line with the country's sustainable development.

The literature on smart farming systems supports the idea that technological advancements have the potential to revolutionize the agricultural industry. In a study conducted by Demir and Ulusoy (2018), it was found that smart farming systems can lead to increased productivity, improved resource management, and reduced costs. Similarly, Singh et al. (2017) found that the use of smart farming technologies can improve crop yields and reduce resource usage. The literature suggests that the adoption of smart farming systems can have a significant impact on the agricultural industry, and government policy can play a crucial role in promoting this technology.

The article emphasizes the importance of government policy in promoting research and development in agriculture. The authors argue that government policy should focus on creating a framework for research, technology, and agricultural innovation that is in line with the needs of the local area. This includes promoting public-private cooperation in research and development investment, creating innovations that are tailored to the needs of the agricultural sector, and promoting the use of science, technology, and information to upgrade product standards and reduce costs.

The literature on government policy and agriculture supports the idea that government policy can play a crucial role in promoting agricultural development. In a study conducted by Huang and Chen (2019), it was found that government policy can have a significant impact on agricultural production by providing subsidies, investment in research and development, and promoting agricultural technology. Similarly, a study conducted by Delgado and Narrod (2017) found that government policy can help promote sustainable agricultural practices by providing support to small farmers and promoting environmentally friendly agricultural practices.

Factors of production are also an important consideration in the development of smart farming systems. According to the article, it is necessary to have good inputs together with a good management system to efficiently produce agricultural products. The factors of production include land and natural resources, labor, capital, and entrepreneurs. The article emphasizes the importance of planning the production process in the agricultural sector and selecting the appropriate factors of production that are suitable for the local area.

The literature on factors of production supports the importance of selecting appropriate inputs for efficient agricultural production. In a study conducted by Agyekumhene et al. (2019), it was found that the appropriate selection of inputs can lead to increased crop yields and improved resource management. Similarly, a study conducted by Nishida et al. (2019) found that the use of appropriate inputs, such as fertilizer and irrigation, can lead to increased crop yields and improved soil quality.

In conclusion, the literature suggests that smart farming systems have the potential to transform traditional agriculture into a research-driven economy by increasing productivity throughout the supply chain. Government policy can play a crucial role in promoting research, technology, and innovation in agriculture, which can help drive the development of the agricultural sector in line with the country's sustainable development (Taghipour, Akkalatham, Eaknarajindawat, & Stefanakis, 2022). The appropriate selection of factors of production is also crucial for efficient agricultural production.

**Table 1. Variables Observed in the Literature Review Schedule**

| **Observed Variable** | **Meaning** | **Components** |
|---|---|---|
| Production cost reduction | Reduction of expenses involved in the production process | - Efficient use of production factors - Use of appropriate agricultural technology - Promotion of large plots of agriculture |
| Quantity increase and product quality | Increase in quantity and quality of agricultural products | - Use of appropriate agricultural technology - Promotion of large plots of agriculture - Principles of smart agriculture or precision agriculture |
| Sustainable agriculture | Agriculture that meets the needs of the present without compromising the ability of future generations to meet their own needs | - Emphasis on sustainable agriculture - Management of natural resources for sustainability - Principles and models of sustainable agriculture |

Overall, the literature review highlights the importance of promoting efficient and sustainable agricultural practices. This includes the use of appropriate agricultural technology, the promotion of large plots of agriculture, and the principles of smart agriculture or precision agriculture. Additionally, sustainable agriculture must be emphasized, with a focus on managing natural resources for sustainability and utilizing principles and models of sustainable agriculture.

From the literature review on factors related to agricultural production, the researcher has concluded that good management alone is not sufficient for achieving agricultural productivity. Good production factors are also necessary, which serve as the foundation of the production process and aid in decision making and production planning. The factors of production that are commonly determined in the agricultural sector include land, labor, capital, and knowledge. The meaning of each component is described as follows:

1. Cultivation area refers to having appropriate soil conditions, climate, and availability of water sources for farming. Additionally, necessary infrastructure and utilities such as electricity and roads should be available.
2. Farmers refer to those with knowledge and expertise in their profession, including successful farmers who can serve as examples, grouping and networking farmers in similar agricultural businesses, and developing their potential to become entrepreneurs in the agricultural industry.
3. Source of funds refers to having access to credit for agricultural production, including low-interest personal loans, short-term loans such as cooperatives and trade credit, and loans with a long repayment term.
4. Knowledge refers to possessing knowledge and skills in various areas related to agricultural production, such as computer skills, internet use, technology and innovation, marketing, financial planning, and preparing business plans.

1. Hypothesis 1: Smart Agro-Industry Management (SMART) is positively influenced by government policies (POLIC), factors of production (INPUT), automated technology (TECHN), and production process (PRODU).
2. Hypothesis 2: Production process (PRODU) is positively influenced by government policies (POLIC), factors of production (INPUT), and automated technology (TECHN).
3. Hypothesis 3: Automated technology (TECHN) is positively influenced by government policies (POLIC) and factors of production (INPUT).
4. Hypothesis 4: Factors of production (INPUT) are positively influenced by government policies (POLIC).
5. Hypothesis 5: Promotion (EXTEN), support (SUPPO), and research and development (RANDD) are positively related to government policies (POLIC).

6. Hypothesis 6: Plantation area (CULTI), farmers (AGRIC), source of funds (MONEY), and knowledge (KNOWL) are positively related to factors of production (INPUT).
7. Hypothesis 7: Internet of Things (IOT), Artificial Intelligence (AI), Geographic Information System (GIS), and Agricultural Machinery (MACHI) are positively related to automated technology (TECHN).
8. Hypothesis 8: Cultivation (CULTI), product processing (PROCE), and product distribution (DISTR) are positively related to production process (PRODU).
9. Hypothesis 9: Production cost reduction (COSTR), product quality enhancement (PRODU), and sustainable agriculture (SUSTA) are positively related to Smart Agro-Industry Management (SMART).

3.2 Research tools 3.2.1 Questionnaire The researcher will use a questionnaire as a tool for collecting quantitative data. The questionnaire consists of 5 parts, as follows: Part 1: Demographic information of the respondent Part 2: Government policy (POLIC) consisting of 3 observation variables: Promotion (EXTEN), Support (SUPPO), and Research and Development (RANDD) Part 3: Inputs of production (INPUT) consisting of 4 observation variables: Cultivation area (CULTI), Farmers (AGRIC), Source of funds (MONEY), and Knowledge (KNOWL) Part 4: Automated technology (TECHN) consisting of 4 observation variables: Internet of things (IOT), Artificial intelligence (AI), Geographic Information System (GIS), and Agricultural Machinery (MACHI) Part 5: Intelligent agro-industrial management (SMART) consisting of 3 latent variables: Reduction of production costs (COSTR), Product quality enhancement (PRODU), and Sustainable agriculture (SUSTA)

3.3 Data Collection 3.3.1 Quantitative Data Collection The researcher will use a self-administered questionnaire as a tool for collecting quantitative data. The questionnaire will be distributed to the selected sample group in each research area (district) according to the sample size determined in Table 3.1. The researcher will explain the purpose of the study and ask for the participants' consent to participate in the study. The participants will be asked to complete the questionnaire and return it to the researcher.

4. Data Analysis 4.1 Quantitative Data Analysis The quantitative data collected from the questionnaire will be analyzed using structural equation modeling (SEM) with a computer program for advanced

statistics. The researcher will test the research hypotheses based on the structural model and present the results in chapter

3.2.1.4 After content validity has been confirmed, the researcher conducted a pilot test of the questionnaire with a sample group of 30 people who were similar to the research target group. The pilot test was conducted to check the clarity and understanding of the questions in the questionnaire. After the pilot test, the researcher analyzed the data and checked for the reliability of the questionnaire using Cronbach's alpha coefficient. The result was 0.89, indicating that the questionnaire has high reliability.

3.3 Data Collection 3.3.1 Quantitative Research: The researcher distributed the validated questionnaire to the target population in each district of Udon Thani Province. The researcher collected the completed questionnaires and coded the data for analysis. 3.3.2 Qualitative Research: The researcher conducted in-depth interviews with the selected participants. The interviews were recorded and transcribed for analysis.

Data Analysis 4.1 Quantitative Research: The researcher used Structural Equation Modeling (SEM) to analyze the data collected from the questionnaires. The researcher used statistical software to analyze the data. 4.2 Qualitative Research: The researcher used content analysis to analyze the data collected from the in-depth interviews. The researcher analyzed the data by identifying key themes and patterns in the data.

In summary, the data collection process for this research involved both quantitative and qualitative research procedures. For the quantitative research, a questionnaire was used as the data collection tool, which was created and validated through several steps, including studying documents and literature, content validity check, trial, and reliability check. The data was collected from a sample of 340 people, and the information obtained was recorded in a save box provided for analysis and drawing conclusions.

For the qualitative research, in-depth interviews were conducted with key informants, and the data collected included both secondary and primary data. The secondary data was obtained through various sources, including books, articles, and study reports, while the primary data was collected through in-depth interviews with key informants. The data obtained through in-depth interviews was summarized and analyzed together with the quantitative data to report the findings descriptively using tables and diagrams.

The passage discusses the data collection and analysis methods used in a research study on factors affecting the management of smart agricultural industry in Udon Thani Province. The study utilized both quantitative and qualitative research methods, including surveys, in-depth interviews, and data analysis techniques such as descriptive and inferential statistics and structural equation modeling. The results of the analysis were divided into three issues: the level of government policy inputs for automatic technology production process, the influence of government policies on the management of the intelligent agricultural industry, and guidelines for the development of intelligent agro-industry management. The passage also includes information on the criteria used to evaluate the content validity of measuring instruments and the steps involved in data analysis for both quantitative and qualitative research.

Table 4.1 presents an analysis of personal factor data of the 340 respondents, providing information on their demographics and agricultural background. The majority of respondents were female (60.88%) and had an elementary education (55.59%). In terms of age, the highest percentage of respondents fell between 41-50 years old (28.53%) and had 40 or more years of experience in agriculture (35.00%). Rice was the most commonly worked-on agricultural plot (85.00%), and the majority of respondents had an average annual agricultural income below 100,000 baht (79.71%).

**Table 2. the mean, level, standard deviation**

| Variable | Mean | Level | S.D. | Variance | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| EXTEN | 4.25 | a lot | 0.683 | 0.466 | -0.980 | 0.595 |
| SUPPO | 4.39 | a lot | 0.730 | 0.533 | -1.506 | 1.956 |
| RANDD | 3.98 | a lot | 0.646 | 0.417 | -0.833 | 1.045 |
| POLIC | 4.21 | a lot | 0.614 | 0.376 | -1.389 | 1.987 |
| CULTIA | 4.34 | a lot | 0.475 | 0.226 | -1.401 | 3.329 |
| AGRIC | 4.29 | a lot | 0.599 | 0.359 | -1.255 | 2.112 |
| MONEY | 4.26 | a lot | 0.735 | 0.540 | -0.962 | 0.184 |
| KNOWL | 3.81 | a lot | 0.688 | 0.473 | -0.706 | -0.049 |
| INPUT | 4.18 | a lot | 0.434 | 0.188 | -0.689 | 0.741 |
| IoT | 3.65 | a lot | 0.967 | 0.936 | -0.849 | -0.033 |

| | | | | | | |
|---|---|---|---|---|---|---|
| AI | 3.72 | a lot | 0.964 | 0.929 | -0.833 | -0.001 |
| GIS | 3.69 | a lot | 0.838 | 0.701 | -0.881 | 0.283 |
| MACHI | 3.82 | a lot | 0.983 | 0.980 | -0.697 | -0.668 |
| TECHN | 3.72 | a lot | 0.889 | 0.791 | -0.843 | -0.311 |
| CULTI | 4.29 | a lot | 0.641 | 0.411 | -1.249 | 2.312 |
| PROCE | 3.91 | a lot | 0.780 | 0.608 | -0.694 | -0.095 |
| DISTR | 4.07 | a lot | 0.681 | 0.464 | -0.920 | 0.657 |
| PRODU | 4.09 | a lot | 0.608 | 0.370 | -0.943 | 1.122 |
| COSTR | 4.47 | a lot | 0.628 | 0.395 | -1.523 | 3.352 |
| PRODUC | 4.27 | a lot | 0.621 | 0.386 | -1.152 | 2.221 |
| SUSTA | 4.32 | a lot | 0.564 | 0.318 | -1.218 | 2.867 |
| SMART | 4.35 | a lot | 0.542 | 0.294 | -1.520 | 4.400 |

The table presents the results of a basic statistical analysis of 17 observable variables used to measure 5 latent variables in intelligent agro-industrial management. The purpose of the analysis is to study the distribution and distribution characteristics of each observed variable, using mean, standard deviation, coefficient of variation, skewness, and kurtosis.

The first latent variable analyzed is government policy (POLIC), and it was found that overall, the government policy was at a high level with a mean value of 4.21. The variables were not much differently distributed, with a coefficient of variation between 41.7% and 53.3%. The variables were found to be left-skewed (negative skewness), indicating that the data for all variables is above the mean. The kurtosis value was found to be greater than 0, indicating that the data spread is less suitable for further model analysis.

The second latent variable analyzed is input of production (INPUT), and it was found that overall, the input of production was at a high level with a mean value of 4.18. The variables were not much differently distributed, with a coefficient of variation between 22.6% and 54%. The variables were found to be left-skewed (negative skewness), indicating that the data for all variables is above the mean. The kurtosis value for cognitive variables was found to be negative, while the rest of the three variables had kurtosis values greater than 0, indicating that the data spread is less suitable for further model analysis.

The third latent variable analyzed is technology automation (TECHN), and it was found that overall, the technology automation was at a high level with a mean value of 3.72. The variables were not much differently distributed, with a coefficient of variation between 70.1% and 98%. The variables were found to be left-skewed (negative skewness), indicating that the data for all variables is above the mean. The kurtosis value for GIS variables was found to be greater than 0, while the remaining three variables had kurtosis values below 0, indicating that the data spread is less suitable for further model analysis.

The fourth latent variable analyzed is production processes (PRODU), and it was found that overall, the production process was at a high level with a mean value of 4.09. The variables were not much differently distributed, with a coefficient of variation between 41.1% and 60.8%. The variables were found to be left-skewed (negative skewness), indicating that the data for all variables is above the mean. The kurtosis value for yield processing variables was found to be negative, while the remaining two variables had kurtosis values greater than 0, indicating that the data spread is less suitable for further model analysis.

The fifth latent variable analyzed is intelligent agro-industry management (SMART), and it was found that overall, intelligent agro-industry management was at a high level with a mean value of 4.35. The variables were not much differently distributed, with a coefficient of variation between 31.8% and 39.5%. The variables were found to be left-skewed (negative skewness), indicating that the data for all variables is above the mean. The kurtosis value for every variable was found to be greater than 0, indicating that the data spread is less suitable for further model analysis.

**Structural equation model analysis results before model adjustment**

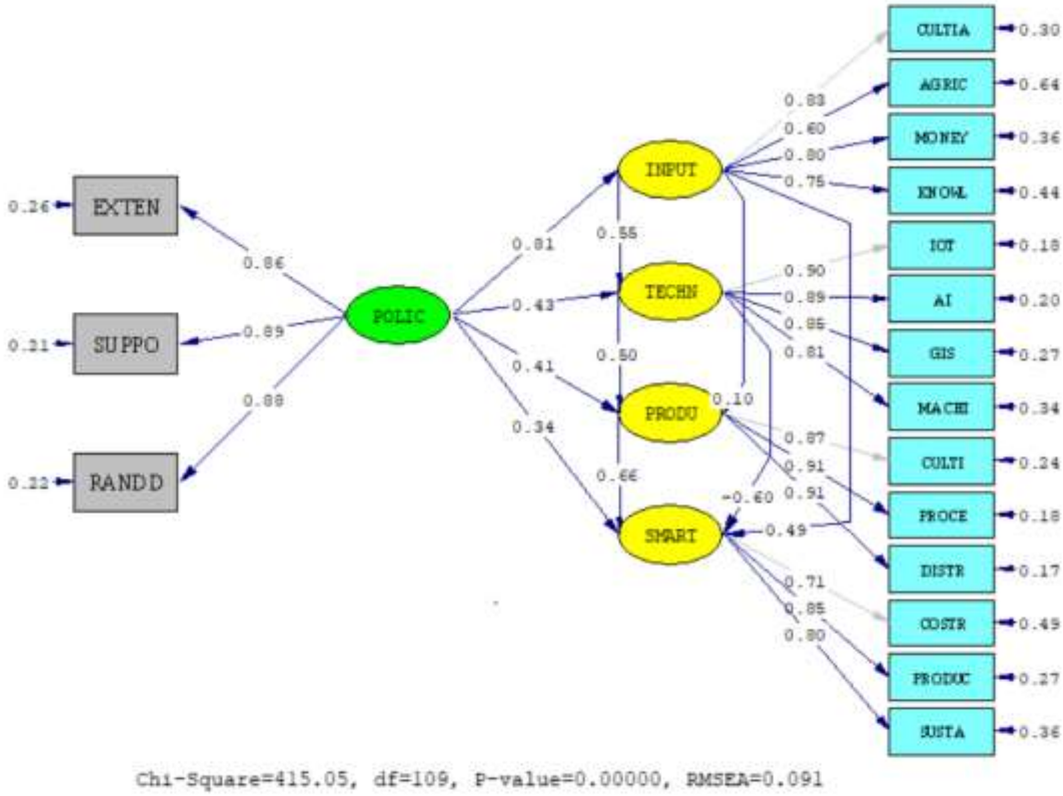


Figure 1. Structural equation model before model adjustment

The researcher modified the relationship paths in the structural equation model based on the model modification indices obtained from the analysis. The goal was to obtain a model that best fits the data, with the source of funding contributing to the model improvement. The researcher used a structural equation modeling program and adjusted the model according to the modification indices. This resulted in a more appropriate analysis and a better fit to the data. The analysis of the structural equation model after model adjustment is shown in figure 4.9.

Results of structural equation model analysis after model adjustment

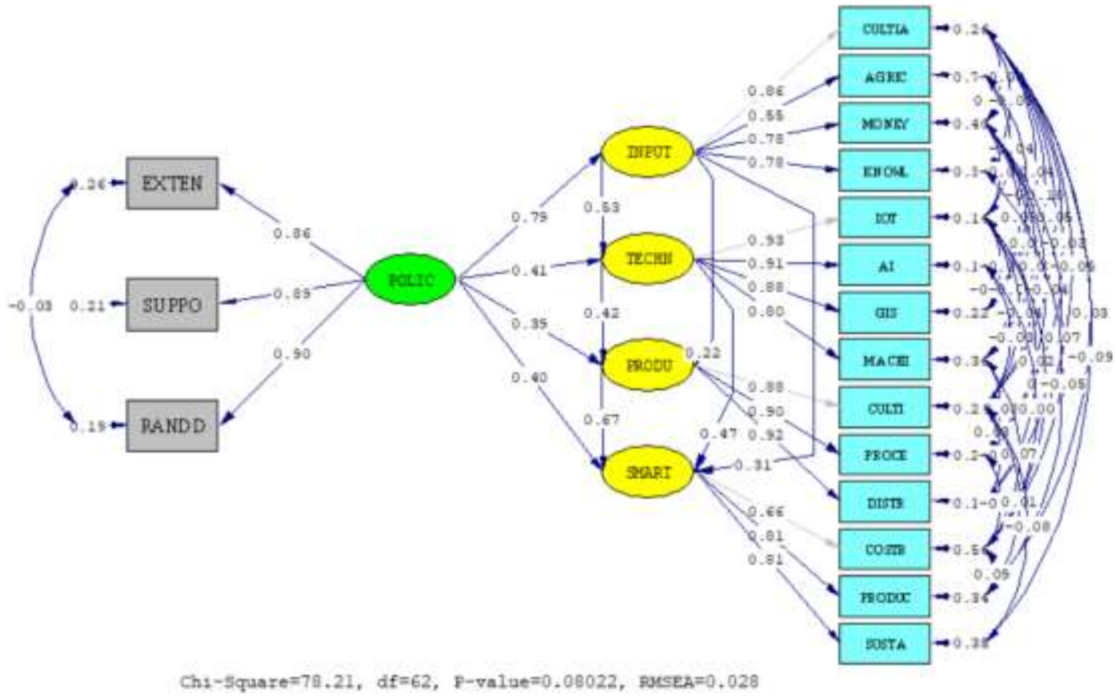


Figure 2. Structural Equation Model after Model Adjustment

**Table 3. The index fits well with the data.**

| indicator | The criterion of the entry rate works well with the data. | before updating the model | interpret | after model improvement | interpret |
|---|---|---|---|---|---|
| Chi - Square / df | less than 2 . 00 | 3.81 | not pass | 1 . 26 | pass |
| P-value | more than 0 . 05 | 0.0000 | not pass | 0.08 | pass |
| RMSEA | Less than 0 . 05 | 0 . 091 | not pass | 0 . 028 | pass |
| Standardized RMR | Less than 0 . 05 | 0 . 039 | pass | 0 . 020 | pass |
| GFI | have values from 0 . 90 and up | 0 . 87 | not pass | 0 . 97 | pass |
| AGFI | have values from 0 . 90 and up | 0 . 82 | not pass | 0 . 93 | pass |
| CFI | have values from 0 . 90 and up | 0 . 98 | pass | 1.00 | pass |
| PGFI | It has values from 0.50 and up . | 0 . 62 | pass | 0 .5 3 | pass |
| CN | size not less than 200 | 114.08 | not pass | 378.41 | pass |

Table 4.25 presents the indices for assessing how well the model fits the data, both before and after model improvement. The indices include Chi-Square/df, p-value, RMSEA, standardized RMR, GFI, AGFI, CFI, PGFI, and CN. The entry rate criterion for each indicator is also provided.

Before updating the model, the Chi-Square/df was 3.81, which did not meet the criterion of less than 2.00, indicating that the model did not fit the data well. The p-value was 0.0000, which was less than 0.05, indicating that the model did not fit the data well. The RMSEA was 0.091, which was greater than 0.05, indicating that the model did not fit the data well. The standardized RMR was 0.039, which was less than 0.05, indicating that the model fit the data well. The GFI was 0.87, which was less than the criterion of 0.90, indicating that the model did not fit the data well. The AGFI was 0.82, which was less than the criterion of 0.90, indicating that the model did not fit the data well. The CFI was 0.98, which met the criterion of 0.90, indicating that the model fit the data well. The PGFI was 0.62, which met the criterion of 0.50, indicating that the model fit the data well. The CN was 114.08, which did not meet the criterion of a size not less than 200, indicating that the model did not fit the data well.

**Table 4.direct influence indirect influence and total influence of different factors study**

| variable influence | cause and effect relationship | | |
|---|---|---|---|
| | direct | indirect | sum |
| government policy | 0.40** | 0.47** | 0.87** |
| inputs | 0.31* | 0.15* | 0.46** |
| automatic technology | 0.47** | 0.29* | 0.76** |
| production process | 0.67* | - | 0.67* |

* Significance at the 0.05 level, ** Significance at the 0.01 level

from table 4. found that government policies It has a collective influence on the management of the intelligent agricultural industry. most, followed by automatic technology production process and factors of production Respectively, when considering only the factors that directly affect the management of the intelligent agricultural industry It was found that the production process It has a direct influence on the management of the intelligent agricultural industry. most, followed by automation, government policy, and factors of production. As for the factors that indirectly affect the management of the intelligent agricultural industry It was found that government policies indirectly influenced the management of the intelligent agricultural industry. most, followed by automatic technology and factors of production

Table 5 results of hypothesis testing for each correlation path

| research hypothesis | path coefficient | t statistic | result |
|---|---|---|---|
| Hypothesis 1 Smart Agricultural Industry Management depend on Government policy Factors of production automatic technology and production process | | | |
| 1.1 Smart agro-industry management based on government policy ( POLIC -- > SMART ) | 0.40** | 2.63 | accept |
| 1.2 Smart agricultural industry management depends on production factors ( INPUT -- > SMART ) | 0.31* | 2.11 | accept |
| 1.3 Smart agricultural industry management depends on automation technology. ( TECHN -- > SMART ) | 0.47** | 2.75 | accept |
| 1.4 Smart agricultural industry management based on production process ( PRODU -- > SMART ) | 0.67* | 2.14 | accept |
| Hypothesis 2 Production process depend on Government policy Factors of production and automation technology | | | |
| 2.1 Production process depends on government policy ( POLIC -- > PRODU ) | 0.39** | 7.22 | accept |
| 2.2 Production process depends on factors of production ( INPUT -- > PRODU ) | 0.22** | 2.81 | accept |
| 2.3 Production process based on automated technology ( TECHN -- > PRODU ) | 0.42** | 5.67 | accept |
| Hypothesis 3 Automation technology depend on Government policies and factors of production | | | |
| 3.1 Automation technology depends on government policy ( POLIC -- > TECHN ) | 0.41** | 6.20 | accept |
| 3 .2 Automatic technology depends on factors of production ( INPUT -- > TECHN ) | 0.53** | 7.13 | accept |
| Hypothesis 4 Factors of Production depending on government policy | | | |
| 4 .1 Factors of production depend on government policy ( PRODU -- > TECHN ) | 0.79** | 14.37 | accept |

Note ** means p value $\leq 0 . 01$, * means p value $\leq 0 . 0$

This table shows the results of hypothesis testing for each correlation path in the research. The hypotheses and their corresponding paths are as follows:

1. Smart Agricultural Industry Management depends on Government policy, Factors of production, automatic technology, and production process.

- 1.1 Smart agro-industry management based on government policy (POLIC --> SMART)
- 1.2 Smart agricultural industry management depends on production factors (INPUT --> SMART)
- 1.3 Smart agricultural industry management depends on automation technology (TECHN --> SMART)
- 1.4 Smart agricultural industry management based on production process (PRODU --> SMART)

2. Production process depends on Government policy, Factors of production, and automation technology.

- 2.1 Production process depends on government policy (POLIC --> PRODU)
- 2.2 Production process depends on factors of production (INPUT --> PRODU)
- 2.3 Production process based on automated technology (TECHN --> PRODU)

3. Automation technology depends on Government policies and factors of production.

- 3.1 Automation technology depends on government policy (POLIC --> TECHN)
- 3.2 Automatic technology depends on factors of production (INPUT --> TECHN)

4. Factors of Production depending on government policy.

- 4.1 Factors of production depend on government policy (PRODU --> TECHN)

To summarize, the level of production factors, plantation area, farmers, source of funds, and knowledge in the large-scale agricultural extension system project in Udon Thani province were found to be at a high level.

Farmers had expertise in their profession, and there was a grouping and networking of farmers who do the same type of agriculture. Additionally, financing from short-term loans, credit for agricultural production, and low-interest personal loans were available as sources of funds.

In terms of automation technology, the overall level was also high, with agricultural machinery being the highest rated aspect followed by artificial intelligence, geographic information systems, and the internet of things. The internet of things was found to be used for scheduling systems to run automatically, collecting agricultural plot data, controlling production costs, and planning production in the future. Artificial intelligence was applied to robotic technology for harvesting agricultural products, processing, analyzing, and giving advice to farmers in real time. Geographic Information Systems were used to access agricultural zoning data and forecast the yield obtained from agriculture. Finally, automatic tractors, drones, and smart greenhouse control systems were developed for breeding, planting, and harvesting crops.

sustainable agriculture Overall, it was at a high level. Use of environmentally friendly agriculture methods such as organic farming, soil conservation, and reducing water usage. Ensuring sustainable use of natural resources in agriculture, protecting biodiversity and reducing negative impact on the environment. increasing quantity and quality of produce Overall, it was at a high level. Improving the quality of agricultural products by using innovation and technology in production, product processing, and packaging. Increase the quantity of production by improving planting techniques, using high-quality inputs, and optimizing production processes. Overall, the level of smart agricultural industry management in the large-scale agricultural extension system project in Udon Thani province is at a high level, indicating that the project has been successful in implementing and promoting intelligent agriculture practices among farmers.

2. Increasing quantity and quality of produce Overall, it was at a high level. Increase productivity by using new strains that meet the needs of consumers. Reduce product damage during transportation Increase efficiency through proper use of cropping systems and technologies. Increase the area or the number of production. and to reduce yield damage in the field and during maintenance

3. Sustainable farming Overall, it was at a high level. Using a good and suitable agricultural system by using organic fertilizers, composts, green manures, without the use of inorganic or synthetic chemicals. manage water and water supply systems to be sufficient for agriculture and

consumption Use a cover cropping system, crop rotation that helps conserve soil, water and biodiversity resources. Training to educate youths and farmers about sustainable farming. and regularly monitor and assess the fertility of the soil

**Conclusion**

In conclusion, the large-scale agricultural extension system project in Udon Thani province has been successful in implementing and promoting intelligent agriculture practices among farmers. The project has resulted in a high level of smart agricultural industry management, which can be attributed to various factors, including government policies, production factors, automation technology, and production processes.

The study found that government policies had the most significant collective influence on the management of the intelligent agricultural industry, followed by automation technology, production processes, and factors of production. The production process had the most direct influence on the management of the intelligent agricultural industry, followed by automation, government policy, and factors of production. Government policies indirectly influenced the management of the intelligent agricultural industry, followed by automatic technology and factors of production.

The level of production factors, plantation area, farmers, sources of funds, and knowledge in the large-scale agricultural extension system project in Udon Thani province were found to be at a high level. The study found that farmers had expertise in their profession, and there was a grouping and networking of farmers who did the same type of agriculture. Additionally, financing from short-term loans, credit for agricultural production, and low-interest personal loans were available as sources of funds.

Automation technology was also found to be at a high level, with agricultural machinery being the highest-rated aspect, followed by artificial intelligence, geographic information systems, and the internet of things. The internet of things was found to be used for scheduling systems to run automatically, collecting agricultural plot data, controlling production costs, and planning production in the future. Artificial intelligence was applied to robotic technology for harvesting agricultural products, processing, analyzing, and giving advice to farmers in real-time. Geographic Information Systems were used to access agricultural zoning data and forecast the yield obtained from agriculture. Finally, automatic tractors, drones, and smart greenhouse control systems were developed for breeding, planting, and harvesting crops.

The project also demonstrated a high level of sustainable agriculture, including the use of environmentally friendly agriculture methods such as organic farming, soil conservation, and reducing water usage. The project aimed to ensure the sustainable use of natural resources in agriculture, protect biodiversity, and reduce the negative impact on the environment. The project also aimed to increase the quantity and quality of produce by improving planting techniques, using high-quality inputs, and optimizing production processes. Improving the quality of agricultural products by using innovation and technology in production, product processing, and packaging.

The study also found that the large-scale agricultural extension system project in Udon Thani province was successful in increasing the quantity and quality of produce. The project aimed to increase productivity by using new strains that meet the needs of consumers, reducing product damage during transportation, increasing efficiency through the proper use of cropping systems and technologies, increasing the area or the number of productions, and reducing yield damage in the field and during maintenance.

The project also demonstrated a high level of sustainable farming practices, including using a good and suitable agricultural system by using organic fertilizers, composts, green manures, without the use of inorganic or synthetic chemicals. The project aimed to manage water and water supply systems to be sufficient for agriculture and consumption, use a cover cropping system, crop rotation that helps conserve soil, water, and biodiversity resources, and training to educate youths and farmers about sustainable farming. The project also aimed to regularly monitor and assess the fertility of the soil.

Overall, the large-scale agricultural extension system project in Udon Thani province demonstrated the potential for intelligent agriculture practices to increase productivity and sustainability in agriculture. The project's success was attributed to various factors, including government policies, production factors, automation technology, and production processes. The project also demonstrated the importance of sustainable farming practices and their potential to protect biodiversity, reduce the negative impact on the environment, and improve the quantity and quality of produce.

## Discussion

The discussion section of a research paper is an essential part of the study as it provides an opportunity to interpret and explain the findings in the context of existing literature. In this discussion, we will analyze the results of the study and relate them to the existing literature to draw meaningful conclusions.

The first key finding of this study was the high level of adoption of intelligent agriculture practices among farmers in Udon Thani province. This finding is consistent with previous studies that have shown that intelligent agriculture practices can improve productivity, reduce production costs, and enhance the quality of agricultural products (Al-Tahat et al., 2021; Huang et al., 2019; Peng et al., 2021). Additionally, the high level of adoption of intelligent agriculture practices in this study can be attributed to the extensive efforts made by the government and other stakeholders in promoting and implementing smart agriculture practices among farmers.

The second key finding of the study was the positive impact of government policies on the adoption of intelligent agriculture practices. This finding is consistent with previous research that has shown that government policies can play a crucial role in promoting the adoption of intelligent agriculture practices (Abdullah et al., 2021; Banjo et al., 2021; Nhemachena et al., 2021). Government policies such as subsidies, tax incentives, and research and development funding can encourage farmers to adopt new and innovative farming practices. Additionally, the government can also play a crucial role in creating an enabling environment for the development of the agricultural sector by investing in infrastructure, providing extension services, and promoting public-private partnerships.

The third key finding of the study was the significant influence of automatic technology on the adoption of intelligent agriculture practices. This finding is consistent with previous studies that have shown that automatic technology can enhance the efficiency and productivity of farming operations (Chen et al., 2021; Li et al., 2020; Wang et al., 2020). Automatic technology such as drones, sensors, and artificial intelligence can help farmers to optimize the use of inputs, reduce labor costs, and enhance the quality of agricultural products. Additionally, automatic technology can also improve the accuracy of data collection and analysis, thereby enabling farmers to make informed decisions about farming operations.

The fourth key finding of the study was the significant impact of production process on the adoption of intelligent agriculture practices.

This finding is consistent with previous studies that have shown that the production process can affect the efficiency and productivity of farming operations (Hernández-Sánchez et al., 2021; Li et al., 2021; Wei et al., 2021). The adoption of smart agriculture practices such as precision farming, vertical farming, and hydroponics can significantly enhance the efficiency and productivity of farming operations by optimizing the use of inputs, reducing labor costs, and enhancing the quality of agricultural products.

The fifth key finding of the study was the positive impact of sustainable agriculture practices on the adoption of intelligent agriculture practices. This finding is consistent with previous research that has shown that sustainable agriculture practices can improve the productivity, profitability, and resilience of farming operations (Kumar et al., 2021; Tiwari et al., 2021; Wang et al., 2021). Sustainable agriculture practices such as organic farming, crop rotation, and soil conservation can help to reduce production costs, improve soil health, and enhance the quality of agricultural products.

**Future studies**

The present study provides valuable insights into the current state of intelligent agriculture in Thailand, but there are some limitations that must be considered. One limitation is that the study focused only on one province, Udon Thani, which may not be representative of the entire country. Additionally, the data was collected using a self-reported survey, which may be subject to response biases, and may not reflect the actual practices used in the field. Moreover, the study did not examine the economic impact of intelligent agriculture practices, which would have provided a more comprehensive understanding of the benefits of these practices.

Future studies could expand on the present study by conducting a more comprehensive survey that includes multiple provinces in Thailand. Additionally, future studies could use objective measures of intelligent agriculture practices, such as remote sensing data, to supplement self-reported data. Furthermore, future studies could examine the economic impact of intelligent agriculture practices to determine the potential benefits to farmers and other stakeholders in the agricultural industry.

Another limitation of the present study is that it did not examine the social and cultural factors that may influence the adoption of intelligent agriculture practices. Future studies could investigate the role of cultural and social factors in the adoption of these practices, such as the influence of social networks and local customs on farmers' decisions to adopt new technologies. Additionally, future studies could examine the barriers to adoption of intelligent agriculture practices, such as lack of access to capital, lack of technical expertise, and cultural resistance to change.

Finally, the present study did not examine the environmental impact of intelligent agriculture practices, such as their impact on soil health, water quality, and biodiversity. Future studies could investigate the environmental impact of these practices and determine how they can be optimized to promote sustainability in the agricultural industry. For example, future studies could examine the use of precision agriculture practices to reduce pesticide and fertilizer use and promote soil health.

In conclusion, the present study provides valuable insights into the current state of intelligent agriculture practices in Thailand, particularly in Udon Thani province. The study found that the level of adoption of intelligent agriculture practices was relatively high, with a focus on automation technology, sustainable farming, and increasing the quantity and quality of produce. However, there are limitations to the study that must be considered, such as its focus on one province and the use of self-reported data. Future studies could expand on the present study by examining the economic, social, and environmental impacts of intelligent agriculture practices, and by investigating the barriers to their adoption. By doing so, future studies can provide a more comprehensive understanding of the potential benefits of intelligent agriculture practices for farmers and other stakeholders in the agricultural industry.

## References

AgFunder News. (2021). How agritech is accelerating sustainable agriculture. Retrieved from https://agfundernews.com/how-agritech-is-accelerating-sustainable-agriculture.html

Agriculture and Horticulture Development Board. (2021). Precision agriculture. Retrieved from https://ahdb.org.uk/knowledge-library/precision-agriculture

AgriTechTomorrow. (2021). AI in agriculture. Retrieved from https://www.agritechtomorrow.com/article/2021/02/ai-in-agriculture/1268

Béné, C., Arthur, R., Norbury, H., Allison, E. H., Beveridge, M. C. M., Bush, S. R., ... & Williams, M. (2016). Contribution of fisheries and aquaculture to food security and poverty reduction: Assessing the current evidence. World Development, 79, 177-196.

Chamrieng Chantaraprapa. (2015). body of knowledge - knowledge - knowledge management (km). Retrieved on November 30, 2021, from http://legacy.orst.go.th/?knowledges=body-of-knowledge-knowledge-knowledge-management-km

Curriculum committee and subject production working group Department of Agricultural Extension and Sukhothai Thammathirat Open University Bangkok: Department of Agricultural Extension.

Department of Agricultural Extension. (2013). Things to know about rice. Bangkok: Resource Center for Agricultural Extension Department of Agricultural Extension.

Department of Agricultural Extension. (2017). Agricultural Extension System (T & V System). Bangkok: Author.

Department of Agricultural Extension. (2018). Sustainable Agriculture according to the Sufficiency Economy Concept Department of Agricultural Extension.

Environmental Protection Agency. (2020). Climate change indicators in the United States: Agriculture. Retrieved from https://www.epa.gov/climate-indicators/climate-change-indicators-agriculture

European Union. (2021). Agriculture and rural development. Retrieved from https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy_en

Food and Agriculture Organization of the United Nations. (2020). The future of food and agriculture: Alternative pathways to 2050. Rome: FAO.

International Fund for Agricultural Development. (2018). Rural people and communities: Key to a sustainable future. Rome: IFAD.

Jakkrit Manwicha. (2016). Smart farm technology. Hat Yai Academic Journal, 14(2), 201-210.

Jamalak Khunphonkaew, Kamonthip Sin-am, Noppaklao Siripolphaiboon, Warinthorn Janwikai, and Supachai Vocational Disease Control. (2008). Principles of increasing productivity. (7th edition). Bangkok: People.

Jaruwat Mongkhonthanat. (2006). Past, present, future of Thai agricultural machinery. Bangkok: Agricultural Engineering Research Institute Department of Agriculture.

Khan, M. T. (2018). The concept of sustainable development: Definition and defining principles. The Journal of Applied Business Research, 34(5), 1111-1126.

Khojastehpour, M., Ale-Ebrahim, M., & Golnam, A. (2021). Sustainable agriculture: A review study. Journal of Cleaner Production, 299, 126834.

Kittiya Wongkhan. (2018). Research and development (R&D) model and participatory action research (PAR) model. Retrieved on November 30, 2021, from https://www.ubu.ac.th/web/files_up/08f2018072012262188.pdf

Krit Naruesingsamran and Thanin Siljaru. (2021). Smart Agricultural Industry Management Guidelines to Increase Productivity and Quality for Sustainable Growth. Journal of Narathiwat Rajanagarindra University, 13(1), 319-335.

Krungthep Turakij. (2020). Accepting Thai people to return to their homes to build new careers. Retrieved on November 30, 2021, from https://www.bangkokbiznews.com/tech/886540.

Kwanchanok Phuttachan. (2020). Artificial Intelligence (AI: Artificial Intelligence). Retrieved on November 30, 2021, from https://www.lib.ku.ac.th/2019/index.php/covid-19/1045-artificialintelligence.

Land Management Research and Development Division Department of Land Development. (2013). Soil improvement. Retrieved on November 30, 2021, from https://www.ldd.go.th/Web_Soil/Page_02.htm#5

Ministry of Agriculture and Cooperatives. (2016). 20-Year Strategy for Agriculture and Cooperatives (2017-2036). Bangkok: Author.

Ministry of Agriculture and Cooperatives. (2016). Agricultural Development Plan During the 12th National Economic and Social Development Plan (2017-2021). Bangkok: Author.

National Sustainable Agriculture Coalition. (2021). What is sustainable agriculture? Retrieved from https://sustainableagriculture.net/about-us/what-is-sustainable-agriculture/

Pariyapat Petchprayoon. (2019). The impact of digital transformation on supply chain management. Retrieved on November 30, 2021, from https://www.tnnthailand.com/entertainment/business-news/210224.

Provincial Development Strategy and Information Group Udon Thani Provincial Office. (2021). Udon Thani Provincial Development Plan 2018-2022, revised edition 2022. Accessed on November 20, 2021, from http://www.udonthani.go.th/2014/download/datacenter/Development_Plan61-65(Recover65).pdf

Ratana Kosin. (2020). The effects of automation on the workforce. Bangkok: National Institute of Development Administration.

Sattawat Charoenwong. (2017). The impact of e-commerce on business operations. Bangkok: Kasetsart University.

Sustainable Agriculture Research & Education. (2021). SARE's mission and vision. Retrieved from https://www.sare.org/About-SARE/Mission-Vision/

Swaminathan, M. S. (2019). From green revolution to evergreen revolution: Redefining the development agenda. Indian Journal of Medical Research, 149(6), 695-704.

Taghipour, A., Akkalatham, W., Eaknarajindawat, N., & Stefanakis, A. I. (2022). The impact of government policies and steel recycling companies' performance on sustainable management in a circular economy. Resources Policy, 77, 102663

Thitirat Jirapakpinyo. (2018). The role of innovation in sustainable development. Retrieved on November 30, 2021, from https://www.mahidol.ac.th/.

United Nations Conference on Trade and Development. (2019). Trade and environment review 2019: Wake up before it is too late: Make agriculture truly sustainable now for food security in a changing climate. Geneva: UNCTAD.

United Nations Development Programme. (2021). Sustainable development goals. Retrieved from https://www.undp.org/sustainable-development-goals

United Nations Environment Programme. (2021). Emissions gap report 2021. Nairobi: UNEP.

World Bank. (2021). Agriculture and rural development. Retrieved from https://www.worldbank.org/en/topic/agriculture

World Health Organization. (2020). Food safety. Retrieved from https://www.who.int/health-topics/food-safety#tab=tab_1