The Effectiveness of Developing Cloud-Based Agricultural Environmental Sensing System to Support Food and Agriculture Education in Elementary School

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***Abstract*—This study developed a cloud-based agricultural environmental sensing framework and system to support traditional food and agricultural education, aiming to overcome the limitations of conventional teaching methods and enhance the learning experience. The system includes solar panels, humidity sensors, temperature sensors, and light sensors, which are sustainable energy components and sensors used to monitor the growth environment of crops. Integrated with Internet of Things (IoT) technology and cloud services, the system can instantly monitor the environment of planted crops, providing students and teachers with critical data on factors affecting crop development. By real-time monitoring of crop growth environments, students and teachers can continuously record and observe the growth of crops, ensuring that the educational process is uninterrupted. To evaluate the effect of the proposed system on students' learning performance in traditional food and agricultural education courses, a quasi-experiment was conducted in an elementary school setting over six weeks, involving two classes. One class served as the control group, engaged in traditional food and agricultural education courses without the proposed system, while the other, the experimental group, was engaged in the courses with the proposed system. The results indicated no significant differences between the experimental and control groups in terms of learning achievements, motivation, or attitudes.**

***Keywords*—food and agricultural education, internet of things, environmental sensing, learning performances, quality education**

I. Introduction

In recent years, global climate change has triggered a food system crisis, causing persistent food safety issues and increasing awareness of the importance of sustainable agriculture and food and agricultural education [1]. A healthy diet is a fundamental human need, crucial to human life, making the focus on "food and agricultural education" from farm to table increasingly important [2]. Agricultural production, as a source of food, affects greenhouse gas emissions, causing environmental pollution [3]. Sustainable agricultural production is essential for achieving food security, reducing malnutrition, and alleviating poverty [4]. Thus, the significance of food and agricultural education lies in addressing unhealthy dietary lifestyles and adopting sustainable food production and consumption practices [5], developing agriculture and dietary cultures suitable for local conditions, and coexisting sustainably with nature.

Food and agricultural education is an experiential learning process that involves students directly participating in agricultural activities, interacting with ingredients, culinary workers, animals, plants, agricultural producers, and the natural environment. This education fosters basic self-sufficiency skills, respect for life, and gratitude, and provides knowledge about local agriculture, proper dietary lifestyles, and their culture, as well as the relationship between agriculture, dietary practices, and the ecological environment [6]. It integrates "dietary culture" and "farming experience", enhancing students' understanding of food sources, encouraging them to try different foods, and improving picky eating habits to foster healthy dietary practices [7]. However, traditional learning approaches face challenges, such as teachers' lack of farming knowledge and the slow growth of crops, alongside considerations for teaching schedules [8]. Parental pressure regarding academic progress [9], and the absence of care for crops during vacations lead to discontinuities in growth records.

To address these challenges, this study developed a cloud-based agricultural environmental sensing system using Internet of Things (IoT) technology to support traditional food and agricultural education. This system, through real-time monitoring and cloud access services, allows students and teachers to overcome the limitations of time and space, continuously recording and observing crop growth, ensuring uninterrupted educational processes. Additionally, the system provides accurate and detailed data on crop growth environments, helping students to deeply understand the factors affecting agricultural production, thereby enhancing their appreciation of sustainable agriculture and food safety.

Integrating IoT technology into food and agricultural education is not only innovative but necessary. By combining IoT technology with the food and agricultural education curriculum, this study offers a novel solution to overcome the limitations of traditional learning approaches. To evaluate the effect of the integrated system on students' learning performance in traditional food and agricultural education courses, a quasi-experiment was conducted in an elementary school setting over six weeks.

II. Literature Review

A. Food and Agricultural Education

Food and agricultural education, through the transmission of experience and knowledge related to diet and agriculture, cultivate a comprehensive learning journey for children and

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consumers that includes local production and consumption, nutrition and safety of ingredients, dietary culture inheritance, agricultural experience, and life education. It enables learners to select ingredients that contribute to a balanced diet for themselves and to reflect on the nutrition, safety, and cultural aspects of the food on their tables. Furthermore, it encourages concern about the sources of food, production methods, and rural environments as part of agricultural education, to cultivate healthy eating habits and agricultural knowledge among students. The importance of food and agricultural education lies in its ability to correct abnormalities in dietary life, allowing people to return to a normal lifestyle and to reassess agriculture, including its natural, social, human, and cultural aspects [10]. It leads to the development of an agricultural style and dietary culture suitable for the locality, sustainably coexisting with nature.

The literature indicates that many schools have joined the ranks of food and agricultural education, primarily to allow students to engage in agricultural experiences [11]. From the planting and growth of crops to the completion of cooking, students learn through physical labor about the difficulty of obtaining food, cultivating a sense of gratitude, and the importance of not wasting food. They gain an understanding of food sources, enhance their ability to choose foods, courageously try different foods, develop habits of not being picky eaters, and improve balanced dietary habits. In learning about farming, they also acquire knowledge and experience related to agriculture and understand what constitutes environmentally friendly farming practices, transitioning from agricultural experience education to environmental education. Education is a long-term internalization process, and the duration of learning, family dietary habits, and other environmental factors can all influence changes in learner behavior [12]. Governments, private sectors, and schools are promoting food and agricultural education through various methods.

Countries have adopted various measures to promote food and agricultural education. For instance, in Japan, the government actively promotes food and agricultural education, analyzing the food education systems and teaching methods of countries like Japan, France, Italy, and others [13]. In the United States, many schools and institutions have implemented food and agricultural education-related projects, such as the Farm to School programs. Studies show that these programs can enhance knowledge about food and nutrition, and positively affect students' healthy food choices during school meals, nutritional self-efficacy, and willingness to try fruits and vegetables [14]. Recently, there has been a development combining service learning with food and agricultural education, using school gardens as campus agricultural areas. During service learning activities, students take care of plants and crops, enhancing their gardening and agricultural skills while using the garden's produce to address the issue of poor nutrition in school lunches [15]. Italy has promoted the innovative nutritional education program MaestraNatura, which aims to increase awareness of healthy foods and lifestyles, promoting the ability to apply the theoretical principles of nutritional guidelines to daily life [16]. These studies indicate that countries are continually striving to promote food and agricultural education. To increase students' awareness and understanding of agriculture and food production, the application of agricultural technology in food and agricultural education is gradually gaining attention.

In Taiwan, the food and agricultural education currently promoted in K-12 schools is primarily focused on agricultural experience education, repurposing unused campus spaces as food and agricultural education zones [17], incorporating essential concepts related to food education in home economics courses [18], and integrating food and agricultural education into daily life to achieve the goal of environmental protection [6]. However, not all teachers at the educational site possess prior knowledge of farming, and the growth of crops does not happen overnight. Challenges such as exams, transitions between semesters or school years, parental pressure regarding academic performance not wanting the food and agriculture curriculum to impact teaching progress [9], or the lack of care and documentation for crops during winter and summer vacations, can lead to discontinuities in the record of growth.

B. Integrating Agricultural Technology into Food and Agricultural Education

Digital agriculture, also known as smart agriculture, has become an important trend in modern agriculture. This form of agriculture utilizes various advanced technological tools, including sensors, robots, digital communication tools, blockchain technology, computational decision-making and analysis tools, and IoT technology, to enhance the efficiency and quality of agricultural production [19]. Controlled environment agriculture, such as greenhouses, indoor farms, vertical farms, and hydroponic farms, are increasingly adopting digital technologies like sensors, robots, and digital communication tools, or using digital, mobile, and IoT technologies to manage and monitor the growth environment of crops [20]. More advanced technologies, such as predictive analytics software and artificial intelligence, have begun to be applied in the field of agriculture. These technologies can utilize vast amounts of data to provide farmers with guidance and recommendations on crop rotation, optimal planting times, harvest times, and soil management. For example, farmers can make more informed decisions based on historical data and weather forecasts with predictive analytics software, improving crop yield and quality. Artificial intelligence technologies can analyze and understand a massive amount of agricultural data through machine learning and deep learning, offering more accurate advice and solutions. The rise of digital agriculture brings new opportunities and challenges to agricultural production. By utilizing advanced technological tools, farmers can more efficiently manage the growth process of crops, increase yield and quality, and better respond to the ever-changing market demands and challenges of climate change [21]. Integrating agricultural technology into elementary school food and agricultural education can help students better understand the processes and technologies behind agricultural production and cultivate their awareness of food production and environmental protection. Furthermore, introducing agricultural technology can enrich the teaching content of food and agricultural education, enhancing student engagement and learning outcomes.

Currently, food and agricultural education integrated with agricultural technology has advanced to include automated irrigation operations or agricultural scheduling. Such automated management of agriculture not only allows students to participate in farming activities but also helps them understand the benefits of technology-assisted cultivation. During winter and summer vacations when no one is available to manage, agricultural scheduling ensures that farmland does not fall into disuse. However, automated processes set in advance may not always align with current weather conditions, or they may not be able to address pest invasions in the garden immediately. Therefore, in addition to automated technology assistance for planting growth, it is essential to continuously record the growth status of crops. Even in the absence of supervision, data collected during the planting period can be analyzed to understand how various factors have influenced the crops, leading to different growth outcomes. This data observation enables the education of students to reflect on what might have caused such harvest conditions.

III. Methodology

A. Agricultural Production Monitoring System

This study designed the agricultural production monitoring system into four distinct sections: Farmland, Environment, Food, and Learners, as illustrated in Fig. 1. Through the farmland, crops are planted, where environmental factors during the planting process impact the growth of the crops either positively or negatively, subsequently affecting the quality and quantity of the food produced. These influencing factors become essential for learners to effectively grasp the critical stages from production to the dining table. Therefore, this study focuses on the development of the agricultural production monitoring system and incorporates IoT technology to continuously and effectively gather, observe, and analyze changes in relevant parameters and their effects on crops and food. It also integrates mechanisms and educational materials for food and agricultural education, allowing for the long-term sustainable operation of this system.

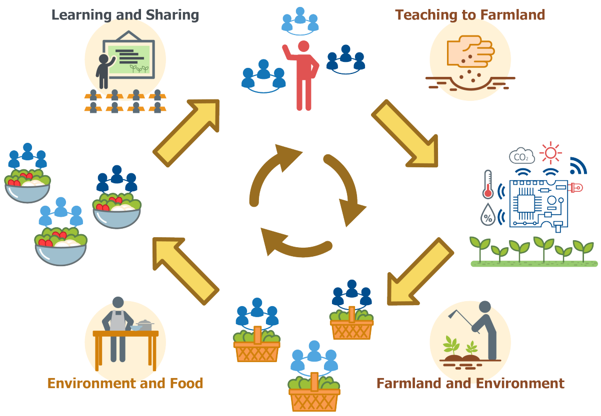


Fig. 1. Agricultural production monitoring system.

Based on the above, to effectively monitor the crop growth environment at the production site and provide real-time monitoring data for teachers and students to observe, this study has planned a cloud-based agricultural environmental sensing structure, as shown in Fig. 2. This structure is primarily divided into the production site, the cloud, and the user endpoint. At the production site, this study uses Arduino and IoT sensors to develop an agricultural box. The agricultural box integrates AM2320 digital temperature and humidity sensors, GY-302 BH1750 light intensity sensor modules, and other components to monitor the crop growth environment. Temperature measurements are taken in Celsius, humidity is measured as relative humidity, and brightness is measured in lux (lx). Additionally, with sustainability in mind, the agricultural box uses solar panels as a renewable energy source. The solar panels convert solar energy into electrical energy stored in lithium batteries, which in turn power the operation of the agricultural box, as illustrated in Fig. 3. The data monitored by the agricultural box are transmitted to the cloud through the ESP8266 wireless network IoT control chip, which uploads the environmental data gathered by the sensors.

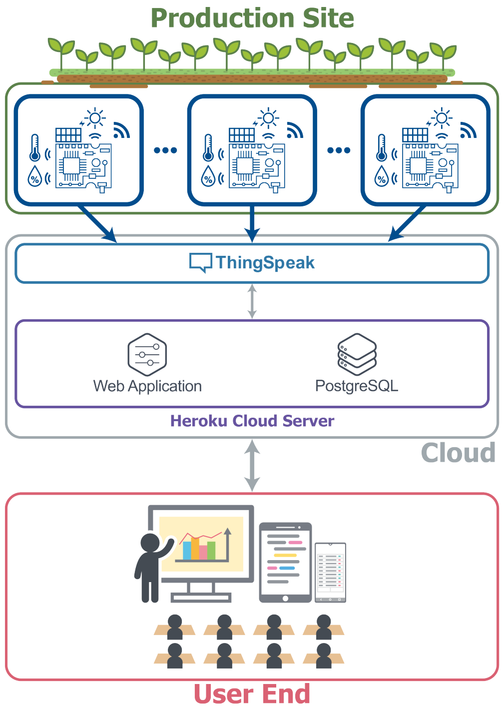


Fig. 2. Cloud-based agricultural environmental sensing structure.

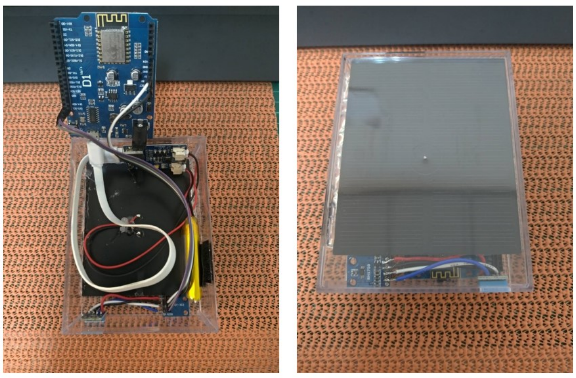


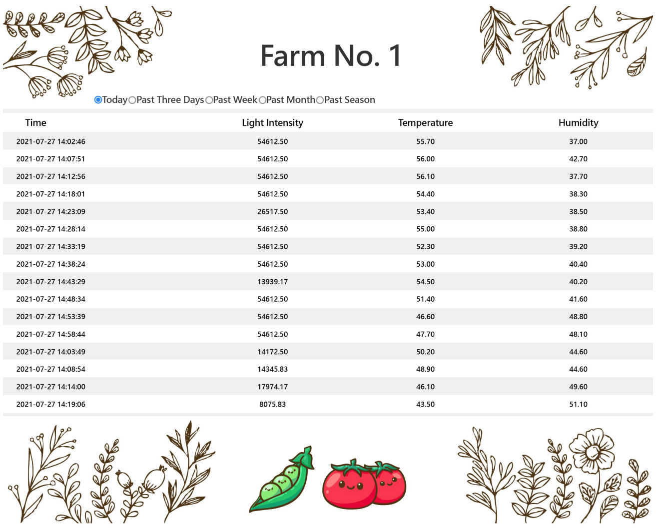
Fig. 3. Internal and external views of the agricultural box.

On the cloud side, to facilitate the storage of data uploaded from the Arduino microcontroller, this study utilized the

ThingSpeak IoT platform as an intermediary interface. To further store and utilize the data uploaded to the ThingSpeak IoT platform, this study developed a web application using the Application Programming Interface (API) provided by ThingSpeak. To offer Software as a Service (SaaS), this study employed a cloud server, Heroku, and set up a cloud database, PostgreSQL, within the cloud server to host the web application developed by this study. This allows for integration with the API provided by the ThingSpeak IoT platform, storing and processing the environmental data from sensors uploaded by the Arduino microcontroller.

On the user end, to facilitate teachers and students in observing the environmental parameters of crop growth on various farmlands at any time, this study developed the aforementioned web application, as shown in Fig. 4. Through the development of the web application, teachers and students can seamlessly access the application using a web browser. The web application allows teachers and students to observe environmental parameters such as temperature, humidity, and light intensity based on the agricultural boxes set up on each farmland. Additionally, it enables the observation of environmental parameters over various time intervals, such as today, the past three days, this week, and the past season, as shown in Fig. 5.

Fig. 4. Web application of the cloud-based agricultural environmental sensing system.



Time	Light Intensity	Temperature	Humidity
2021-07-27 14:02:46	54612.50	55.70	37.00
2021-07-27 14:07:51	54612.50	56.00	42.70
2021-07-27 14:12:56	54612.50	56.10	37.70
2021-07-27 14:18:01	54612.50	54.40	38.30
2021-07-27 14:23:09	26517.50	53.40	38.50
2021-07-27 14:28:14	54612.50	55.00	38.80
2021-07-27 14:33:19	54612.50	52.30	39.20
2021-07-27 14:38:24	54612.50	53.00	40.40
2021-07-27 14:43:29	13939.17	54.50	40.20
2021-07-27 14:48:34	54612.50	51.40	41.60
2021-07-27 14:53:39	54612.50	46.60	48.80
2021-07-27 14:58:44	54612.50	47.70	48.10
2021-07-27 14:03:49	14172.50	50.20	44.60
2021-07-27 14:08:54	14345.83	48.90	44.60
2021-07-27 14:14:00	17974.17	46.10	49.60
2021-07-27 14:19:06	8075.83	43.50	51.10

Fig. 5. Observation interface for crop growth environmental parameters.

B. Experimental Design

To evaluate the impact of the proposed system integration into traditional food and agricultural education courses on student learning performances, this study plans a quasi-experimental design in an elementary school's food and agricultural education curriculum. The curriculum design philosophy emphasizes connecting with the land, cultivation, consumption, and recycling, initiating a farmland maker journey to comprehend the essence of the land, understand plant growth, experience the value of ingredients, and manage a sustainable environment. This teaching activity continues for 6 weeks (480 min), involving two classes (totaling 43 elementary students) and one teaching teacher. One class with 22 students serves as the control group, and the other class with 21 students as the experimental group. The control group is taught using the traditional food and agricultural education curriculum, while the experimental group receives instruction through the integration of the proposed system into the traditional food and agricultural education curriculum.

1) Research instruments

To evaluate the effectiveness of the proposed approach, this study utilizes data collected from a prior knowledge test, learning achievement test, learning motivation questionnaire, and learning attitude questionnaire for analysis. The prior knowledge test is designed to evaluate students' knowledge about food and agricultural education before participating in the course instruction, while the learning achievement test evaluates the students' learning outcomes after course participation. Both tests are designed by two teachers with five years of experience teaching food and agriculture education to ensure expert validity. Each test consists of 10 multiple-choice questions, with a total score of 100.

The learning motivation questionnaire adopts the intrinsic motivation scale from the Motivated Strategies for Learning Questionnaire (MSLQ) [22], used to measure students' goals and beliefs regarding the importance and interest of the teaching activities of this course. This questionnaire has been used by many researchers to measure the learning motivation of students participating in information technology-supported teaching activities [23, 24]. The learning motivation questionnaire contains 9 questions, using a 7-point Likert scale, and the reliability (Cronbach's alpha coefficient) of the results filled out by all students participating in this experiment is 0.830.

To measure students' learning attitudes, this study uses a learning attitude questionnaire developed from the learning attitude scale [25, 26], used to measure students' learning attitudes towards the teaching activities they participated in. The learning attitude questionnaire contains 7 questions, using a 4-point Likert scale, and the reliability of the answers to the learning attitude questionnaire by all students participating in this experiment is 0.803.

2) Experimental procedure

Fig. 6 illustrates the experimental process conducted in this study. Before the official course instruction, students from both the experimental and control groups were invited to participate in three pre-tests, totaling 30 min. The first two tests involved answering questionnaires on learning motivation and learning attitude to measure the students' motivation and attitude towards learning before instruction. The third test was a prior knowledge test designed to evaluate whether the two groups of students had equal levels of knowledge about food and agricultural education. Furthermore, the teacher spent 30 min explaining the teaching activities to both groups of students, and an additional 20 min introducing the system developed in this study to the experimental group students.

During the 370-min teaching process, both groups of students participated in teaching activities planned by this study and the teacher. Each teaching unit started with activities designed to arouse motivation, leading students into the activity development. Initially, before planting vegetable crops, the teacher sparked students' motivation to grow their own vegetables by discussing food safety issues and their impact on health. Then, students were introduced to and discussed types of vegetables, the suitable seasons for planting vegetables, and how to grow them, leading to the students starting to prepare the land for planting. The experimental group students also set up the agricultural boxes developed in this study; during the vegetable cultivation and care stage, the teacher introduced how to care for the growing vegetable crops, how to water and fertilize, and the effects of pests and diseases on vegetable crops, guiding students to observe and record the growth process of the vegetable crops. The experimental group students could also use the system developed in this study to observe environmental factors such as light, humidity, and temperature affecting the growth of vegetable crops. When it was time to harvest the vegetable crops, the teacher taught students how to harvest the planted vegetables and observed the harvested crops, discussing the results of the harvest through the recorded growth process. Finally, they discussed the ways to consume the vegetable crops and fostered the concept of cherishing resources and valuing food among the students.

After completing all teaching units and activities, both the experimental and control groups of students conducted three post-tests, totaling 30 min: the learning motivation questionnaire, the learning attitude questionnaire, and the learning achievement test, to complete the experiment conducted in this study.

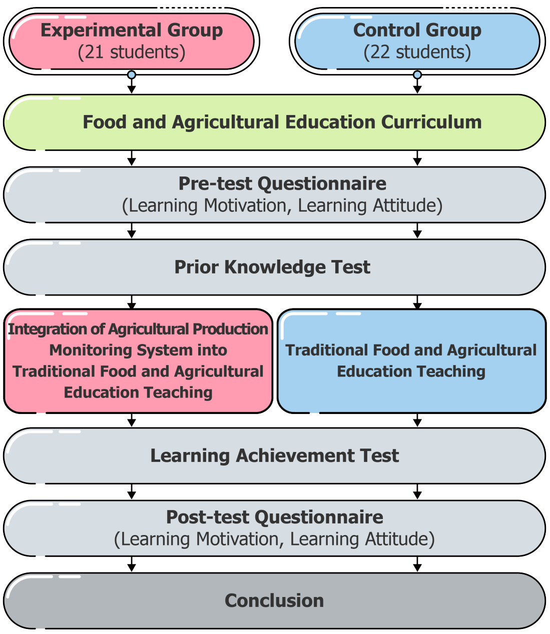


Fig. 6. Experimental procedure.

IV. Result

Based on the data collected from the aforementioned experimental design, the experimental results are analyzed to discuss the impact of the proposed approach on students' learning outcomes, learning motivation, and learning attitudes from various aspects.

A. Analysis of Learning Achievement

To evaluate whether there were significant differences in the prior knowledge of food and agricultural education between two groups of students before participating in the educational activities planned in this study, an independent samples *t*-test was used to compare the mean differences in prior knowledge test scores between the two groups. The independent samples *t*-test is used to determine if there are significant differences in the means of two samples. A descriptive statistical analysis of the data collected from the prior knowledge test indicated that the mean score for the experimental group was 50.95 with a standard deviation of 17.86, while the control group had a mean score of 46.36 with a standard deviation of 12.55. Before conducting the *t*-test, it was necessary to verify if the samples were normally distributed. Given that the sample size in this experiment was less than 50, the Shapiro-Wilk test was used to check for normal distribution, which yielded a value of 0.065 ($p > 0.05$). This *p*-value tests whether the variance between the two groups shows significant differences; a *p*-value greater than 0.05 indicates that there is no significant difference in prior knowledge between the two groups, thus confirming the sample satisfies the assumption of normal distribution. The *Levene*'s test for equality of variances showed no significant result ($F = 2.27$, $p = 0.135 > 0.05$), indicating that the variances within groups were considered equal. After confirming that the sample was normally distributed and that the variances within groups were equal, the independent samples *t*-test was conducted to examine if there was a significant difference in the prior knowledge test scores between the two groups, as shown in Table 1. The analysis results showed no significant difference in the prior knowledge test scores between the experimental and control groups ($t(41) = 0.978$, $p = 0.334 > 0.05$). This result indicates that the two groups of students had equal prior knowledge of food and agricultural education before participating in the learning activities.

Table 1. Analysis of the prior knowledge test results between experimental group students and control group students using independent samples *t*-test

Group	*N*	Mean	SD	*t(41)*	*p*-value
E	21	50.95	17.86	0.978	0.334
C	22	46.36	12.55	-	-

E: Experimental Group; C: Control Group; SD: Standard Deviation

To further investigate the effect on student learning outcomes, this study employed one-way Analysis of Covariance (ANCOVA) as the method for analyzing the results of the learning achievement test. ANCOVA was chosen because it allows for adjusting the effects of students' initial differences in prior knowledge, ensuring that any changes in learning achievement can be attributed more accurately to the intervention rather than prior knowledge levels. By setting the learning achievement test results as the dependent variable and the prior knowledge test results as the covariate, ANCOVA helps to isolate the effect of the educational intervention by controlling for variability in students' prior knowledge, thus providing a more precise assessment of the intervention's impact on learning outcomes. The regression coefficient met the homogeneity of regression assumption ($F = 0.116$, $p = 0.735 > 0.05$). Table 2 presents the results of the one-way ANCOVA for the learning achievement test scores of the experimental and control groups. The adjusted mean and standard error for the experimental group were 69.40 and 3.79, respectively, and 67.84 and 3.70 for the control group. The analysis indicated a significant difference in the adjusted learning achievement test scores between the experimental and control group students ($F(1,40) = 0.086$, $p = 0.771 > 0.05$), with the experimental group students outperforming the control group students. However, this result shows that the integration of the system proposed in this study into the food and agricultural education curriculum did not result in a statistically significant difference in student learning achievements compared to students who participated in the food and agricultural education curriculum without the integration of the system proposed by this study.

Table 2. One-way analysis of covariance of the learning achievement test results between experimental group students and control group students

Group	*N*	Mean	SD	Adj. Mean	Adj. SE	*F*	*p*-value
E	21	69.52	16.57	69.40	3.79	0.086	0.771
C	22	67.72	16.57	67.84	3.70	-	-

E: Experimental Group; C: Control Group; SD: Standard Deviation; SE: Standard Error

B. Analysis of Learning Motivation

This analysis aims to evaluate whether there was a significant difference in learning motivation between the two groups of students before participating in the teaching activities planned in this study. Data collected from the pre-test learning motivation questionnaire were first subjected to descriptive statistical analysis. The average score for the experimental group students was 5.33 with a standard deviation of 0.94, while the control group students had an average score of 5.75 with a standard deviation of 0.54. To evaluate whether there were differences in learning motivation between the two groups of students before participating in the teaching activities, this study used an independent samples *t*-test to compare the mean differences in pre-test scores for learning motivation between the two groups. Given that the sample size of this experiment was less than 50, the Shapiro-Wilk test was initially used to check if the samples followed a normal distribution, with a result of 0.955 ($p > 0.05$), indicating that the samples met the assumption of normal distribution. Subsequently, *Levene*'s test for equality of variances showed no significant result ($F = 4.02$, $p = 0.052 > 0.05$), indicating that the variances within groups were considered equal. An independent samples *t*-test was then conducted to examine if there was a significant difference in the pre-test scores for learning motivation between the two groups, as shown in Table 3. The results indicated no significant difference in the pre-test scores for learning motivation between the experimental and control groups ($t(41) = -1.790$, $p = 0.081 > 0.05$). This result suggests that the two groups of students had equal learning motivation for food and agricultural education before participating in the teaching activities.

To evaluate the effect of the system proposed in this study on students' learning motivation in participating in the food and agricultural education course, this study employed one-way ANCOVA as the method for analyzing the results of the learning motivation questionnaire. This was aimed at eliminate the impact of the pre-test results on the post-test results, setting the post-test results of learning motivation as the dependent variable and the pre-test results as the covariate. The regression coefficient met the assumption of homogeneity ($F = 1.054$, $p = 0.311 > 0.05$). Table 4 presents the results of the one-way ANCOVA for the learning motivation test scores of the experimental and control groups. The adjusted mean and standard error for the experimental group were 5.75 and 0.24, respectively, and 6.09 and 0.24 for the control group. The analysis indicated no significant difference in the adjusted learning motivation scores between the experimental and control group students ($F(1,40) = 0.916$, $p = 0.344 > 0.05$). This result demonstrates that the integration of the system proposed in this study into the food and agricultural education curriculum does not have a significant difference in student learning motivation compared to students who participated in the food and agricultural education curriculum without the integration of the system proposed by this study.

Table 3. Analysis of the pre-test results for learning motivation between experimental group students and control group students using independent samples *t*-test

Group	*N*	Mean	SD	*t(41)*	*p*-value
E	21	5.33	0.94	−1.790	0.081
C	22	5.75	0.54	-	-

E: Experimental Group; C: Control Group; SD: Standard Deviation

Table 4. One-way analysis of covariance of the post-test results for learning motivation between experimental group students and control group students

Group	*N*	Mean	SD	Adj. Mean	Adj. SE	*F*	*p*-value
E	21	6.13	0.94	5.75	0.24	0.916	0.344
C	22	5.71	1.25	6.09	0.24	-	-

E: Experimental Group; C: Control Group; SD: Standard Deviation; SE: Standard Error

C. Analysis of Learning Attitude

This analysis aimed to evaluate whether there was a significant difference in learning attitudes between the two groups of students before participating in the planned teaching activities of this study. Data collected from the pre-test learning attitude questionnaire underwent descriptive statistical analysis. The average score for the experimental group students was 3.16 with a standard deviation of 0.45, while the control group students had an average score of 3.37 with a standard deviation of 0.37. To assess differences in learning attitudes between the two groups before participating in the teaching activities, this study used an independent samples *t*-test to compare the mean differences in pre-test scores for learning attitudes between the two groups. As the sample size of this experiment was less than 50, the Shapiro-Wilk test was initially employed to check if the samples followed a normal distribution, yielding a result of 0.955 ($p > 0.05$), indicating that the samples met the assumption of normal distribution. Subsequently, *Levene*'s test for equality of variances showed no significant result ($F = 0.248$, $p = 0.621 > 0.05$), indicating that the variances within groups were considered equal. Therefore, an independent samples *t*-test was conducted to examine if there was a significant difference in the pre-test scores for learning attitude between the two groups, as shown in Table 5. The results indicated no significant difference in the pre-test scores for learning attitude between the experimental and control groups ($t(41) = -1.691$, $p = 0.098 > 0.05$). This result suggests that the two groups of students had equal learning attitudes towards food and agricultural education before participating in the teaching activities.

Table 5. Analysis of the pre-test results for learning attitude between experimental group students and control group students using independent samples *t*-test

Group	*N*	Mean	SD	*t(41)*	*p*-value
E	21	3.16	0.45	–1.619	0.098
C	22	3.37	0.37	-	-

E: Experimental Group; C: Control Group; SD: Standard Deviation

To evaluate the impact of the system proposed in this study on students' learning attitudes within the food and agricultural education curriculum, this study utilized one-way ANCOVA to analyze the results of the learning attitude questionnaire. This approach was chosen to eliminate the influence of pre-test results on post-test outcomes, setting the post-test learning attitude results as the dependent variable and the pre-test results as the covariate. The regression coefficient satisfied the homogeneity assumption ($F = 1.054$, $p = 0.311 > 0.05$). Table 6 presents the results of the one-way ANCOVA for the learning attitude test scores of both the experimental and control groups. The adjusted mean and standard error for the experimental group were 3.57 and 0.11, respectively, and 3.32 and 0.11 for the control group. The analysis revealed no significant difference in the adjusted learning attitude scores between the experimental and control group students ($F(1,40) = 2.257$, $p = 0.141 > 0.05$). This result indicates that integrating the proposed system into the food and agricultural education curriculum does not significantly affect student learning attitudes compared to students who participated in the curriculum without the system integration.

Table 6. One-way analysis of covariance of the post-test results for learning attitude between experimental group students and control group students

Group	*N*	Mean	SD	Adj. Mean	Adj. SE	*F*	*p*-value
E	21	3.56	0.48	3.32	0.11	2.257	0.141
C	22	3.33	0.56	3.57	0.11	-	-

E: Experimental Group; C: Control Group; SD: Standard Deviation; SE: Standard Error

This study proposed a cloud-based agricultural environmental sensing system, utilizing IoT technology to support traditional food and agriculture education courses. However, no significant differences were found in learning achievements, motivation, or attitudes between the experimental and control groups. Further investigation is needed to understand why this is the case and what factors may have influenced the results.

The proposed system in this study did not change the learning activities and content of the traditional food and agriculture education courses. Its primary function was to provide monitoring of crop growth environments as a supplementary tool, assisting teachers in maintaining continuous observation of the crops during school breaks and holiday periods, and assisting both teachers and students in observing the relationship between crops and their growth environments. Schools involve students in experiencing agricultural tasks from crop growth to the completion of cooking, enabling students to recognize the difficulty of acquiring food, cultivating a sense of gratitude, and understanding the principle of not wasting food. However, the system developed in this study is primarily used for monitoring crops. While it can solve the problem of continuous observation of crops during vacations, it only serves as a monitoring tool and does not directly intervene in the teaching content, making it difficult to directly affect students' learning processes or arouse their interest in learning. This assistance facilitated the observation of the relationship between crops and their growing environments by teachers and students. However, the learning objectives of food and agriculture education go beyond understanding agricultural production and the cultivation experience of crop growth; more importantly, from farm to table, changing consumer awareness [27], and further promoting nutritionally balanced healthy eating habits. The formation of these habits is a long-term internalization process, and environmental factors such as the duration of learning and family dietary habits can affect learners' behavior [12], but it may be difficult to assess these aspects from the perspectives of learning achievements, motivation, and attitudes. Therefore, it may not be possible to explain the effectiveness of the system proposed in this study from the perspectives of student learning achievements, motivation, and attitudes. Furthermore, even with the advent of new technologies such as IoT cloud monitoring systems, if teachers are unable to effectively integrate the system into the curriculum, students may find it difficult to adapt and understand the impact of this technology on food and agriculture education activities. With lower technology acceptance, this might undermine the positive impact on the learning process, resulting in overall learning outcomes that do not meet expected results [28].

Cloud-based agricultural environmental sensing systems demonstrate that IoT technology in education is not limited to agricultural education [29]. Its applications can extend to other natural environment-related educational settings. IoT systems can be used to monitor and analyze various environmental data, helping students engage in real-time data analysis and experimental research, enhancing their scientific literacy and experimental skills [30]. Furthermore, students can use sensing systems to monitor local ecological environments, engage in environmental protection projects, and understand the impact of human activities on the environment, thus enhancing their environmental awareness and responsibility. In smart campus development, cloud sensing systems can be applied to campus management, such as energy monitoring, security systems, and automated classroom management, improving the quality and safety of campus management [31].

Education needs more interdisciplinary integration and innovation. IoT, Artificial Intelligence (AI), and big data technologies can be combined with educational systems to provide personalized learning experiences and precise instructional support, requiring teachers to possess certain technological skills and to adjust educational policies and curriculum designs to support these new technologies [32]. Meanwhile, in the context of rapid technological development, educators should actively explore and implement new technologies, creating a more diverse range of learning opportunities for students. To effectively implement these technologies in the classroom, teachers need to understand and address potential challenges, and adopt corresponding strategies to overcome them. For example, integrating technology like IoT, AI, and big data is more challenging in traditional subjects that lack the use of these technologies. Beyond training teachers to enhance their informational capabilities [27], considering interdisciplinary teaching approaches is also advisable. When teachers aim to integrate Information Technology (IT) into the classroom, they may face the challenge of how to align IT with educational objectives. Effective use of information tools can also help teachers develop teaching materials [33]. It is recommended that teachers start with educational goals and choose appropriate IT tools [34–36]. AI can be used to assist in personalized teaching analysis, while IoT can be utilized to perform experimental operations by collecting data, integrating technology into teaching, rather than adapting teaching to technology [37]. The learning approach of using IT in education may pose challenges for students, potentially leading to decreased classroom engagement due to unfamiliarity with IT [38], thus affecting learning outcomes. In addition to adjusting systems based on students' information capabilities, simplifying system tools and adding more guidance can help students adapt to technology-integrated learning modes [39].

The duration of this study and the methods of data collection could influence the significance of the results. This study was limited by a small sample size and a short duration of intervention, which may not have been sufficient to observe significant changes in student motivation and attitudes. Additionally, whether the data collection methods accurately reflect students' actual learning situations is another important factor affecting the results. Future research should involve more detailed control and optimization in these areas, such as conducting long-term studies on the impact of technology use on various learning aspects or experimenting with larger and more diverse populations to more accurately assess the effectiveness of new technologies in food and agriculture education.

V. Discussion

The results of this study show no significant differences between the experimental and control groups of students in terms of learning achievement, motivation, and attitude. Regarding these results, this study discusses that the system developed did not alter the main teaching activities and content of traditional food and agricultural education but served as an auxiliary tool for teachers and students. Schools allow students to experience the farming process, helping them realize the challenges in obtaining food, fostering a sense of gratitude, and the importance of not wasting food. However, the learning objectives of food and agriculture education, besides understanding agricultural production and crop growth experiences, are more crucially about changing consumer awareness [27], from farm to table, and promoting the development of healthy eating habits with balanced nutrition. The formation of these habits is a long-term internalization process, influenced by factors such as the duration of learning and family dietary habits [12]. However, it is challenging to assess these aspects through learning achievement, motivation, or attitudes. Therefore, the effects generated might not be observable from the aspects of achievement, motivation, and attitude. Additionally, while integrating IT into learning can provide learners with diverse ways to acquire new knowledge, some studies suggest that certain factors in technology integration may increase cognitive load, making it difficult for learners to internalize what they have learned [40]. Cognitive load theory defines the total cognitive load of a learning task as the sum of the intrinsic and extraneous loads present in the task [41]. Intrinsic load is influenced by the complexity and difficulty of the learning content itself and is not manipulated by instructional design, while extraneous load refers to the cognitive load generated by ineffective design in presenting learning content [42]. Therefore, cognitive load theory advocates avoiding unnecessary design and focusing on actual learning, as changing teaching methods without adequate preparation could lead to confusion and stress for students and teachers [43]. However, in various studies on technology integration in learning, some results have shown that detailed visual information or interactive feedback generated by learning applications may induce cognitive load and decrease motivation, but they can also have a positive effect on learning [44]. During the process of integrating emerging technologies into teaching, teachers using instructional strategies that reduce cognitive load and employing a structured and autonomy-supportive motivational style can help lessen students' cognitive loads and enhance their self-regulation motivation, engagement, and academic achievement. Structured information helps to minimize distractions, and autonomy support, which is related to engagement, allows students to focus their attention on the required learning activities, thereby reducing the proportion of irrelevant cognitive loads [45].

VI. Conclusion

This study developed a cloud-based agricultural environmental sensing framework and system to support traditional food and agricultural education courses. It integrates IoT technology and cloud services, allowing for real-time sensing of the growth environment of planted crops and enabling teachers and students to observe the growth environmental parameters of crops anytime and anywhere. The aim is to enhance students' understanding of crop growth, thereby deepening their knowledge of food and agricultural education from aspects such as land, crops, environment, and food.

The cloud-based agricultural environmental sensing framework and system developed in this study hoped to use solar power as the main energy source for sustainable operation. However, due to the current global climate extremes, the frequency of consecutive hot days or heavy rainfall is higher, leading to the system components being more susceptible to overheat due to continuous hot days or the lithium batteries not being able to charge adequately due to insufficient sunlight, causing the system to malfunction. Therefore, system administrators still need to regularly check the system's operational status to ensure that it can provide normal environmental monitoring services for the planted crops. Despite these challenges, the application of IoT in agriculture remains a highly effective approach, offering real-time data and automation that can significantly enhance farming efficiency. With proper implementation and maintenance, IoT technology represents a promising alternative that can revolutionize agricultural practices, making them more resilient and adaptable to changing environmental conditions. Future research efforts will continue to integrate the proposed system into curriculum teaching, not only for monitoring purposes but also incorporating structured learning information to facilitate easier classroom use by teachers, thereby reducing cognitive load for students.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors conducted the research, wrote the paper, analyzed the data, revised and edited the paper; all authors had approved the final version.

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