

Students' Acceptance of Applying Internet of Things in a Smart Agriculture Course*

WEN-JYE SHYR, CHIN-CHUNG HUANG, CHIA-HUNG CHEN and JHIH-SYUAN WEI

Department of Industrial Education and Technology, National Changhua University of Education, No. 1, Jin-De Road, Changhua 500, Taiwan, R.O.C. E-mail: shywj@cc.ncue.edu.tw

This study applied the technology acceptance model (TAM) to an Internet of Things (IoT) smart agriculture course, and used IoT teaching module and textbooks. Taking the students at a technical high school as the objects, it helps students to develop IoT concepts, improves students' learning outcomes, and achieves the teaching goals of the IoT smart agriculture course. This study adopted independent sample t test, reliability analysis, and regression analysis, and used SmartPLS to measure the structure models for analysis. The results include the applications of the technology acceptance model to the IoT smart agriculture course. The equipment used was IoT teaching module and textbooks, which has high learning satisfaction. There is correlation between the dimensions of the technology acceptance model, and all hypotheses are valid and achieve significant levels.

Keywords: internet of things (IoT); smart agriculture; technology acceptance model (TAM); teaching strategies

1. Introduction

Under the condition of rapid technical evolution, sensing technology-related hardware and software are advancing by leaps and bounds. Moreover, due to the applications and developments of the Internet, the increasingly rapid transmission speed accelerates the development of the Internet of Things (IoT). In the IoT environment, people and objects, objects and machines, and even objects and objects can communicate with each other over the Internet.

With the development of the digital learning theory and action learning technology, many new learning models and study topics have emerged [1–3], such as the theory of reasoned action (TRA), the theory of planned behavior (TPB), and the unified theory of acceptance and use of technology (UTAUT). Davis [4] proposed the technology acceptance model (TAM), and successfully explored user acceptance of various information systems in many fields, which has been widely verified [5]. Scholars commonly use the TAM to examine the impact of attitudes and behavioral intentions. For example, perceived usefulness and perceived ease were important predictors of internet adoption [6–8].

The uses of prototypes and related methods such as problem, design and project oriented approaches have been used in engineering education. Based on student self-evaluation surveys, these methods have been successful [9, 10]. Karvinen and Karvinen [11] presented a setup for rapid IoT prototyping in a classroom, identified necessary skills and combined these to a workshop that allows students to turn their ideas into prototypes.

The purpose of the IoT smart agriculture course is to develop students' awareness of IoT and the concept of smart agriculture, in order to establish the basis and interest of students in IoT smart agriculture. Students can easily edit programs on tablet computers and learn how to write Block and JavaScript programs through the teaching module, in order to improve the effectiveness of programming language teaching and enhance learners' specialized knowledge in software systems.

The IoT teaching module is used as the teaching equipment and TAM is imported to explore the purposes and outcomes of the technical high school students in using teaching modules. Based on the above study background and motivation, the purposes of this study are to explore students' acceptance of applying internet of things in a smart agriculture course.

2. Literature Review

2.1 Internet of Things (IoT)

IoT integrates various devices and facilities, including mobile terminals embedded with various sensing components, and building security and escape systems, intelligent housing systems, and intelligent vehicle-mounted systems, and many such systems are combined with various sensors. The overall concept is divided into 3 layers, as based on different application properties, including the perception layer, network layer, and application layer. By integrating the three-layer architecture, various devices and facilities are connected to each other through the network to exchange information and transmit control commands [12].

As the bottom layer of the three-layer architecture, namely “Things”, the perception layer consists of device sensing signals that can monitor the physical conditions of an environment, such as temperature, humidity, and illumination. Through various sensing components, such as sensors, RFIDs, and 2D barcodes, it collects environmental data or monitors the environment, and conducts remote control, setting, operation, and management. Moreover, it has the characteristics of low energy consumption, low cost, and support a large number of network nodes [13].

The network layer is the second layer, which includes wired and wireless network techniques, as well as cloud application technology, and with the reliable network transmission function, it makes all installed devices or facilities have the transmission function. The network layer is mainly used to receive data from the perception layer, and transmit them to the application layer. Through various network technologies, the data obtained by the sensing components can be transmitted to specific people, events, or things, and the data collected by devices or facilities can be integrated into the data management center. Hence, the communication protocol of the network layer must be compatible and provide a secure and stable network environment [14].

The application layer is the one closest to real life. Through effective analysis and processing, disorganized data can be formed into useful information for efficient application. The application is considered after objects are connected to each other, and efficiency analysis and evaluation are conducted on the different states and different data collected. The data from the sensors of all devices or facilities are collected for business logic classification and analytical judgment, and relevant services are provided [15].

2.2 Smart Agriculture

The Industry 4.0 has become an important concept as well as direction in the industrial and social development [16]. It provides educational set up and educational task that could be used as practical exercise in a number of undergraduate engineering courses. Initial assignments are given to the students, including, monitoring of indoor environment, monitoring of water quality and smart agriculture. In smart agriculture, the IoT concept and technology are mainly used to upload the collected and captured sensing data (e.g., temperature, humidity, luminance, carbon dioxide, soil moisture, and insect attack) to the cloud database using farms' existing physical objects (e.g., agricultural machines, agricultural facilities, soil, and crops), importing sensing components (e.g., biosen-

sing, environmental sensing, and image recognition), and combining the wireless communication technology. Data are converted into useful information for agricultural operation through big data exploration, integration, and analysis, and provided as a reference for farm managers to make operating decisions, such as production and marketing planning, production management, and customer services, in order to assist in intelligent monitoring during production and marketing, reduce farms' burdens and labour demands, establish more effective farm operations and management modes, and produce safe, secure, and traceable agricultural products that satisfy consumer demands.

2.3 IoT Teaching Module

In order to allow students to learn more about IoT, programming, and the maker movement, some companies have launched IoT teaching module, which integrates the cloud, modules, devices, and software. Simply by using the plug-and-play technology of teaching equipment and downloading relevant applications, users can remotely control and learn how to design IoT devices via mobile devices, such as smart phones or tablet computers. Mobile devices can be used for direct programming. By directly operating physical components through the network and cloud platform, all learners who intend to enter the IoT field can learn the IoT concepts in the most intuitive and fast manner, and combine various sensors or other components to make their own intelligent cloud. Bernstein et al. [17] indicated that after participating in teaching module, students more likely to utilize learned principles within academia and industry. Overall, the results indicate that critiquing student projects within a specific context, such as sustainability, can be an effective learning strategy.

2.4 Technology Acceptance Model (TAM)

TAM is proposed based on TRA. TAM can be used to explore the acceptance of students applying the IoT teaching module to the smart agriculture course. Theory of reasoned action (TRA) [18, 19] was used to forecast or understand human purposes and behaviors from the perspective of social psychology, and is widely used in studies in various fields. Student attrition in engineering is of concern. Paimin et al. [20] investigated motivational factors necessary to succeed in engineering. The TRA model was used to guide the suggested paths from learning strategy, interest, and intention to academic performance.

Theory of planned behavior (TPB) is an extension of TRA, and the individual performance of a specific behavior in this framework is controlled by

the forecast of 3 variables: personal attitude, subjective norm, and perceived behavior [21]. Specifically, while TRA identifies one's attitude and social perceptions toward performing a behavior as predictors of an individual's behaviors, TPB extends it by including perceived behavioral control or an individual's beliefs regarding the possession of required skills to perform a given behavior [22, 23]. TAM mainly simplifies TRA and focuses on explaining users' acceptance of new information technology in computer technology, in order to analyze the effects of user acceptance. Its purpose is to explain and forecast the usage behaviors of information system users and simplify TRA, in particular, the focus is on the users' acceptance of new information technology in computer technology.

In TAM, perceived usefulness and perceived ease of use are independent variables, and users' attitudes and behavioral intentions to use are dependent variables. It claims that perceived usefulness and perceived ease of use will affect the attitude to use technology, and thus, affect specific behaviors, and that the use of information technology is affected by behavioral intention to use. Perceived usefulness and perceived ease of use are mainly applied to explain and infer user attitudes and behavioral intention to use, and perceived usefulness and perceived ease of use are affected by external variables [24]. The dimensions of TAM are defined, as follows:

2.4.1 External Variables

External variables are the factors affecting users' adoption of information technology, including users' individual differences, individual situations, individual behaviors, self-expression, system characteristics, and environmental variables.

2.4.2 Perceived Usefulness

Perceived usefulness refers to the increased degree of job performance when users use the system. In organizations, people can obtain better efficiency through pay raises, promotions, awards, and other rewards [25]. When a system has good perceived usefulness, it indicates that users believe the system has better utilization efficiency.

2.4.3 Perceived Ease of Use

Perceived ease of use is the degree to which users can easily use it without working harder. Ease of use refers to avoiding difficulties or very large effort; effort refers to allocating limited resources that users can bear.

2.4.4 Attitude Toward Using

Attitude toward using is to measure users' positive

or negative feelings in implementing systems, and is affected by perceived usefulness and perceived ease of use.

2.4.5 Behavioral Intentions to Use

Behavioral intentions to use are to measure users' strength in performing specific behaviors.

3. Teaching Design Model and Teaching Strategies

This study applied the IoT teaching module to the IoT smart agriculture course according to the ADDIE (analysis, design, development, implementation, and evaluation) teaching design model, which is described as follows:

3.1 Analysis

Technical high school students were taken as the subjects (a total of 32 people), and a tablet, projector, computer, IoT teaching module, and broadband network were provided in the teaching environment. The students have basic information operation capacities and basic IoT concepts.

3.2 Design

According to the analysis stage and considering the learning goals, select the various components for smart agriculture and design IoT smart agriculture courses suitable for students.

3.3 Development

According to the results of analysis and design, make briefs, assemble the teaching module, edit the software program, and develop the study lists.

3.4 Implementation

Implementation considers how to set up the teaching activities and teaching environment. This course gives priority to physical demonstrations, which are supplemented by briefs, in order that students can easily learn and operate.

3.5 Evaluation

Use the study lists to evaluate students' learning and match the TAM scale for analysis.

3.6 Teaching strategies

Teaching strategies are the teacher-student-oriented systems. Teaching strategies generally refer to the methods, procedures, and technologies of teachers' use of textbooks, which use various procedures and technologies. Moreno and Flowerday [26] argued that computer-based teaching can draw students' attention. Teaching strategies refer to the fact that teachers consider various teaching models to achieve teaching goals. Teaching strate-

gies are specific, diverse, and task-oriented, and consist of direct and indirect teaching, connections among the evaluations of oriented teaching strategies, questioning strategies, and class management strategies. Direct teacher-oriented teaching and indirect student-oriented teaching are used as the teaching strategies. Consistency between teaching strategies and students' achievements can arouse students' learning motivations and interest, build students' confidence and expression, strengthen students' abilities to solve problems independently, and improve teaching and learning efficiencies.

4. Research Design and Implementation

According the literature review in technology acceptance model (TAM), the variables proposed by this study are perceived enjoyment (external variables), perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention to use. On this basis, a TAM scale for IoT smart agriculture is developed.

4.1 Participate

A total of 32 students from a technical high school were taken as the objects.

4.2 Research Implementation

The teaching outcomes of the IoT smart agriculture course was explored by using TAM, and the teaching duration of the smart agriculture course was 2

weeks, with 6 hours per week and 12 hours in total. A quantitative questionnaire based on TAM was used as the main test tool.

4.3 Research Tools

The questionnaire of Chen et al. [27] provided reference for the research tools, indicating good scale reliability. The measurement was based on a Likert 5-point scale, ranging from 5 (strongly agree), 4 (agree), 3 (unsure), 2 (disagree) to 1 (strongly disagree).

After the questionnaire was completed, scholars and experts in education and technology were invited to review the questionnaire and suggest corrections, in order to construct expert content validity. After the data of the questionnaire regarding the current usage status of the smart agriculture course were sorted, a TAM scale was developed and divided into 5 dimensions: perceived enjoyment, perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention to use. There are 4 items for each dimension and 20 items in total.

4.4 Reliability and Validity Analysis of the Scale

The pretest scale of TAM and the Cronbach's α coefficient was 0.841, which shows internal consistency. In addition, inappropriate questions were deleted after the scale items were analyzed, and the KMO value was 0.52 after item analysis by SPSS. The factor analysis was conducted to build scale validity. Table 1 shows the item analysis of the

Table 1. Item analysis for pretest scale of TAM

Item	Critical ratio	Correlation to the total score of the scale	α value after this item is deleted	Commonality	Factor loading
1	2.16***	0.33***	0.83	0.61	0.51
2	2.34***	0.23***	0.83	0.78	0.83
3	4.58***	0.47***	0.82	0.74	0.49
4	2.54***	0.32***	0.83	0.86	0.57
5	3.00***	0.37***	0.83	0.83	0.84
6	2.89***	0.40***	0.83	0.75	0.53
7	1.52***	0.35***	0.83	0.78	0.63
8	1.52***	0.14***	0.84	0.88	0.89
9	2.34***	0.29***	0.83	0.82	0.81
10	2.70***	0.37***	0.83	0.78	0.84
11	6.06***	0.70***	0.81	0.68	0.52
12	1.71***	0.17***	0.84	0.82	0.84
13	3.86***	0.61***	0.82	0.79	0.78
14	2.25***	0.31***	0.83	0.82	0.83
15	2.37***	0.34***	0.83	0.74	0.55
16	3.12***	0.54***	0.82	0.79	0.77
17	2.57***	0.38***	0.83	0.91	0.91
18	2.82***	0.48***	0.82	0.73	0.75
19	3.63***	0.58***	0.82	0.82	0.52
20	5.00***	0.65***	0.81	0.71	0.57

*** $p < 0.001$.

pre-test questionnaire, and the results are, as follows:

- (1) In the pretest scale of TAM, according to the total score, with the first 27% as the high-score group and the last 27% as the low-score group, mean difference test (t-test) was carried out to solve the critical ratios (CRs) of all items. In this study scale, any item failing to reach the significance level of $p < 0.05$ was recommended for deletion. All items reached the significance level of $p < 0.05$, and were reserved.
- (2) The properties of the factor loadings were similar to those of regression coefficients, and the values show the effects of such items on the potential variables of this questionnaire. When the factor loading is above 0.71, it indicates that this factor can explain 50% of the variations of the observable variables, which is an ideal condition; if the factor loading is less than 0.32, it is a very unsatisfactory condition, indicating that this item's contribution is very small and should be deleted.

5. Data Analysis

Questionnaire survey on the smart agriculture course was conducted with students, and statistical analysis software SPSS and SmartPLS 2.0 were used for data analysis and processing. In order to solve the problems explored, independent sample t

testing, regression analysis, and path equation were adopted in this questionnaire for analysis, and the results are summarized, as follows:

5.1 Descriptive Statistics for the Questionnaire Scale of TAM

Table 2 shows the data collected from the TAM scale of this questionnaire.

- (1) In the perceived enjoyment dimension of this TAM scale, the maximum average mean is 4.56 and the minimum average mean is 4.12, which indicates that students are interested in learning IoT technology and are motivated to learn.
- (2) Regarding perceived usefulness dimension, the maximum average mean is 4.38 and the minimum average mean is 4.13, which indicates that students generally agree that it is helpful for learning performance of IoT technology and future development.
- (3) Regarding perceived ease of use dimension, the maximum average mean is 4.25 and the minimum average mean is 4.00, which indicates that students can accept and learn IoT module operation and are willing to learn.
- (4) Regarding attitude toward using dimension, the maximum average mean is 4.44 and the minimum average mean is 4.28, which indicates that students generally agree that the evaluation of IoT technology learning is positive.

Table 2. Descriptive statistics of the TAM questionnaire

Dimension	Item	Average mean	Standard deviation (SD)
Perceived enjoyment	1. When learning IoT module, I forget the passing of time	4.25	0.57
	2. When learning IoT module, I take no particular notice whether my surroundings are noisy	4.12	0.49
	3. The IoT module is fun to use	4.44	0.56
	4. The IoT module can trigger my interest in learning	4.56	0.50
Perceived usefulness	5. I think IoT module can improve my learning outcomes	4.16	0.81
	6. I think IoT module can improve my learning ability	4.38	0.55
	7. I think it is useful to learn IoT module	4.13	0.66
	8. I think IoT module can increase my learning efficiency	4.16	0.63
Perceived ease of use	9. The interfaces of IoT module are clear and understandable	4.25	0.62
	10. The software of IoT module is easy to use	4.00	0.62
	11. The hardware of IoT module is easy to use	4.09	0.64
	12. The links between software and hardware of IoT module are easy to learn	4.16	0.68
Attitude toward using	13. I think IoT module is a great system to use	4.28	0.63
	14. The IoT module course is satisfactory	4.44	0.56
	15. The IoT module is a good way to learn	4.34	0.55
	16. I love the course using IoT module for learning	4.34	0.65
Behavioral Intentions to use	17. I am willing to use IoT module for learning	4.13	0.61
	18. I feel happy when using IoT module for learning	4.09	0.53
	19. I would like to increase the frequency of using IoT module for learning	4.31	0.54
	20. I hope I still can use IoT module for learning in the future	4.38	0.55

N = 32.

Table 3. Reliability analysis of perceived enjoyment

Items of the scale	Correlation to the total score of the scale	Cronbach's α after this item is deleted	Cronbach's α
1. When learning IoT module, I forget the passing of time	0.336	0.629	0.637
2. When learning IoT module, I take no particular notice whether my surroundings are noisy	0.377	0.595	
3. The IoT module is fun to use	0.578	0.439	
4. The IoT module can improve my interest in learning	0.392	0.585	

- (5) Regarding behavioral intentions to use dimension, the maximum average mean is 4.38 and the minimum average mean is 4.09, which indicates that students are generally interested and willing to use the IoT module.

5.2 Questionnaire Reliability Analysis

Regarding the TAM scale of the questionnaire, the Cronbach's α coefficient of internal consistency is 0.81, indicating good internal consistency of the scale.

5.2.1 Reliability Analysis of Perceived Enjoyment

The reliability analysis of perceived enjoyment in this questionnaire shows that Cronbach's α value is 0.637, which indicates that this questionnaire meets the standard of high reliability. The reliability analysis results are shown in Table 3.

5.2.2 Reliability Analysis of Perceived Usefulness

The reliability analysis of perceived usefulness in this questionnaire shows that Cronbach's α coefficient is 0.769, which indicates that this questionnaire meets the standard of high reliability. The reliability analysis results are shown in Table 4.

5.2.3 Reliability Analysis of Perceived Ease of Use

The reliability analysis of perceived ease of use in

this questionnaire shows that Cronbach's α coefficient is 0.753, which indicates that this questionnaire meets the standard of high reliability. The reliability analysis results are shown in Table 5.

5.2.4 Reliability Analysis of Attitude Toward Using

The reliability analysis of attitude toward using in this questionnaire shows that Cronbach's α coefficient is 0.789, which indicates that this questionnaire meets the standard of high reliability. The reliability analysis results are shown in Table 6.

5.2.5 Reliability Analysis of Behavioral Intentions to Use

The reliability analysis of behavioral intentions to use in this questionnaire shows that Cronbach's α coefficient is 0.767, which indicates that this questionnaire meets the standard of high reliability. The reliability analysis results are shown in Table 7.

5.3 Regression Analysis of the TAM Scale

5.3.1 Regression Analysis between Perceived Enjoyment and Perceived Usefulness

The relationship between the independent variable "perceived enjoyment" and the dependent variable "perceived usefulness" is explored by using SPSS

Table 4. Reliability analysis of perceived usefulness

Items of the scale	Correlation to the total score of the scale	Cronbach's α after this item is deleted	Cronbach's α
5. I think IoT module can increase my learning outcome	0.637	0.676	0.769
6. I think IoT module can improve my learning ability	0.507	0.746	
7. I think it is useful to learn IoT module	0.544	0.727	
8. I think IoT module can increase my learning efficiency	0.603	0.698	

Table 5. Reliability analysis of perceived ease of use

Items of the scale	Correlation to the total score of the scale	Cronbach's α after this item is deleted	Cronbach's α
9. The interfaces of IoT module are clear and understandable	0.587	0.675	0.753
10. The software of IoT module is easy to use	0.522	0.712	
11. The hardware of IoT module is easy to use	0.550	0.695	
12. The links between software and hardware of IoT module are easy to learn	0.545	0.700	

Table 6. Reliability analysis of attitude toward using

Items of the scale	Correlation to the total score of the scale	Cronbach's α after this item is deleted	Cronbach's α
13. I think IoT module is a great system to use	0.600	0.737	0.789
14. The IoT module course is satisfactory	0.545	0.762	
15. The IoT module is a good way to learn	0.603	0.737	
16. I love the course using IoT module for learning	0.651	0.709	

Table 7. Reliability analysis of behavioral Intentions to use

Items of the scale	Correlation to the total score of the scale	Cronbach's α after this item is deleted	Cronbach's α
17. I am willing to use IoT module for learning	0.627	0.678	0.767
18. I feel happy when using IoT module for learning	0.519	0.736	
19. I would like to increase the frequency of using IoT module for learning	0.526	0.733	
20. I hope I still can use IoT module for learning in the future	0.600	0.694	

regression analysis. The results are shown in Table 8. As seen, the significance is $p = 0.000 < 0.001$, which is a significant difference. Hence, the hypothesis is supported, and the valid hypothesis indicates that perceived enjoyment has significant effects on perceived usefulness.

5.3.2 Regression analysis between perceived enjoyment and perceived ease of use

The relationship between the independent variable “perceived enjoyment” and the dependent variable “perceived ease of use” is explored using SPSS regression analysis. The results are shown in Table 9, where the significance is $p = 0.000 < 0.001$, which

is a significant difference. Hence, the hypothesis is supported, and the valid hypothesis indicates that perceived enjoyment has significant effect on perceived ease of use.

5.3.3 Regression Analysis between Perceived Usefulness and Attitude Toward Using

The relationship between the independent variable “perceived usefulness” and the dependent variable “attitude toward using” is explored using SPSS regression analysis, and the results are shown in Table 10. As seen, the significance is $p = 0.000 < 0.001$, which is a significant difference. Hence, the hypothesis is supported, and the valid hypothesis

Table 8. Regression analysis between perceived enjoyment and perceived usefulness

	Unstandardized coefficient		Standardized coefficient	t	Significance
	Estimated value of B	Standard error	Beta distribution		
Perceived enjoyment	0.070	0.192		0.365	0.717
	0.980	0.044	0.972	22.45	0.000***

*** $p < 0.001$, $F = 503.99$, $R^2 = 0.942$.

Table 9. Regression analysis between perceived enjoyment and perceived ease of use

	Unstandardized coefficient		Standardized coefficient	t	Significance
	Estimated value of B	Standard error	Beta distribution		
Perceived enjoyment	0.010	0.318		0.033	0.974
	0.989	0.072	0.929	13.760	0.000***

*** $p < 0.001$, $F = 189.344$, $R^2 = 0.859$.

Table 10. Regression analysis between perceived usefulness and attitude toward using

	Unstandardized coefficient		Standardized coefficient	t	Significance
	Estimated value of B	Standard error	Beta distribution		
Perceived usefulness	0.349	0.217		1.609	0.118
	0.925	0.050	0.959	18.645	0.000***

*** $p < 0.001$, $F = 347.633$, $R^2 = 0.918$.

Table 11. Regression analysis between perceived ease of use and attitude toward using

	Unstandardized coefficient		Standardized coefficient	t	Significance
	Estimated value of B	Standard error	Beta distribution		
Perceived ease of use	0.778	0.303		2.568	0.015
	0.832	0.069	0.910	12.017	0.000***

*** $p < 0.001$, $F = 144.407$, $R^2 = 0.822$.

Table 12. Regression analysis between attitude toward using and behavioral intentions to use

	Unstandardized coefficient		Standardized coefficient	t	Significance
	Estimated value of B	Standard error	Beta distribution		
Attitude toward using	0.442	0.398		1.111	0.276
	0.903	0.091	0.875	9.889	0.000***

*** $p < 0.001$, $F = 97.784$, $R^2 = 0.757$.

indicates that perceived usefulness has significant effect on attitude toward using.

5.3.4 Regression analysis between perceived ease of use and attitude toward using

The relationship between the independent variable “perceived ease of use” and the dependent variable “attitude toward using” is explored using SPSS regression analysis, and the results are shown in Table 11, where the significance is $p = 0.000 < 0.001$, which is a significant difference. Hence, the hypothesis is accepted, and the valid hypothesis indicates that there is significant difference between perceived ease of use and attitude toward using.

5.3.5 Regression Analysis between Attitude Toward Using and Behavioral Intentions to Use

The relationship between the independent variable “attitude toward using” and the dependent variable “behavioral intentions to use” is explored using SPSS regression analysis, and the results are

shown in Table 12. As seen, the significance is $p = 0.000 < 0.001$, which is a significant difference. Hence, the hypothesis is accepted, and the valid hypothesis indicates that attitude toward using has significant effect on behavioral intentions to use.

5.4 TAM Model Validation

The significance testing was conducted on the structural model using SmartPLS 2.0 software to explore whether the hypotheses were valid. In PLS, the R^2 values are mainly used to test the forecasting abilities of the structural paths. The R^2 values refer to the percentage of the variations that can be explained by dependent variables after independent variables are inserted, and represent the forecasting ability of the study model. The resampling frequency was set at 2000 to test the significance of all paths, and the TAM validation results are shown in Fig. 1.

The results indicate that perceived usefulness and perceived ease of use have strong explanatory

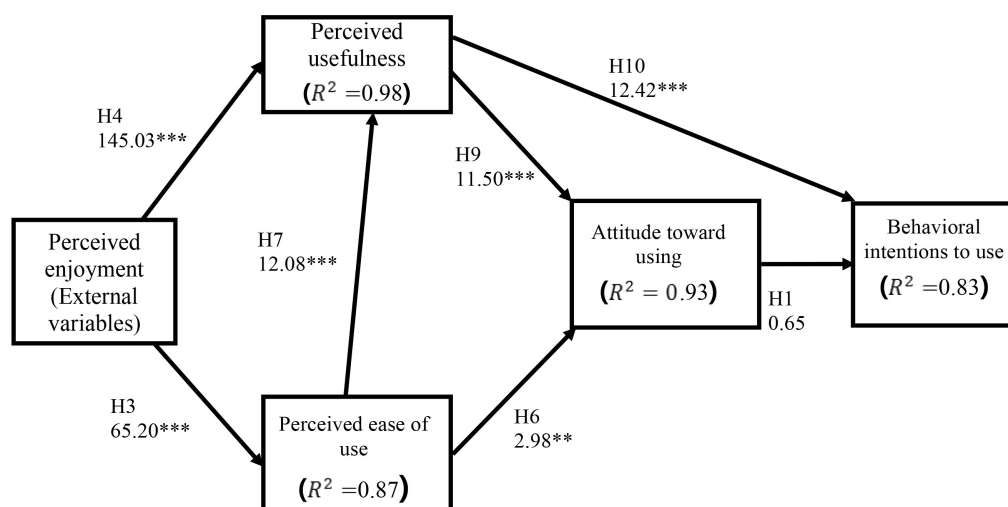


Fig. 1. TAM validation results (** $p < 0.01$, *** $p < 0.001$).

Table 13. Test results of relationships among variables

Hypothesis / relationship between variables	Path coefficient (β)	t value	Test result
H1: Attitude toward using \rightarrow Behavioral Intentions to use	0.06	0.65	Unsupported
H2: Perceived enjoyment \rightarrow Attitude toward using	0.72	92.89***	Supported
H3: Perceived enjoyment \rightarrow Perceived ease of use	0.93	65.20***	Supported
H4: Perceived enjoyment \rightarrow Perceived usefulness	0.44	145.03***	Supported
H5: Perceived enjoyment \rightarrow Behavioral Intentions to use	0.38	22.60***	Supported
H6: Perceived ease of use \rightarrow Attitude toward using	-0.69	2.98**	Supported
H7: Perceived ease of use \rightarrow Perceived usefulness	0.57	12.08***	Supported
H8: Perceived ease of use \rightarrow Behavioral Intentions to use	0.04	8.62***	Supported
H9: Perceived usefulness \rightarrow Attitude toward using	1.64	11.50***	Supported
H10: Perceived usefulness \rightarrow Behavioral Intentions to use	0.86	12.42***	Supported

** $p < 0.01$, *** $p < 0.001$.

power regarding attitude toward using ($R^2 = 0.93$); and attitude toward using also has strong explanatory power regarding behavioral intention to use ($R^2 = 0.83$). In addition, perceived enjoyment (external variable) has strong explanatory power regarding perceived usefulness ($R^2 = 0.98$) and perceived ease of use ($R^2 = 0.87$).

The relationship among all variables is shown in Table 13. In the 10 hypotheses, except for H1, the other variables reach the significant level. The hypothesis report shows that attitude toward using has not significantly positive effect on behavioral intention to use (H1) ($\beta = 0.06$, $p > 0.05$); and perceived enjoyment has significantly positive effect on attitude toward using (H2) ($\beta = 0.44$ (H4) * 1.64(H9) = 0.72, $p < 0.001$), perceived ease of use (H3) ($\beta = 0.93$, $p < 0.001$), perceived usefulness (H4) ($\beta = 0.44$, $p < 0.001$), and behavioral intention to use (H5) ($\beta = 0.44$ (H4) * 0.86(H10) = 0.38, $p < 0.001$). Perceived ease of use has significantly positive effect on attitude toward using (H6) ($\beta = -0.69$, $p < 0.01$), and perceived usefulness (H7) ($\beta = 0.57$, $p < 0.001$), and behavioral intention to use (H8) ($\beta = 0.04$, $p < 0.001$). Finally, perceived usefulness has significantly positive effect on attitude toward using (H9) ($\beta = 1.64$, $p < 0.001$) and behavioral intention to use (H10) ($\beta = 0.86$, $p < 0.001$).

6. Discussion

This study used TAM by incorporating IoT teaching module as well as integrating technology acceptance and learner satisfaction. The overall results did support the influence of teaching module to contribute to the critique of this psychological education theory.

In the TAM questionnaire of IoT smart agriculture, as developed and built, the dimensions consist of perceived enjoyment (external variable), perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention to use, and the study results are, as follows:

- (1) Attitude toward using has not significantly effect on behavioral intention to use.
- (2) Perceived enjoyment has significantly positive effect on attitude toward using.
- (3) Perceived enjoyment has significantly positive effect on perceived ease of use.
- (4) Perceived enjoyment has significantly positive effect on perceived usefulness.
- (5) Perceived enjoyment has significantly positive effect on behavioral intention to use.
- (6) Perceived ease of use has significantly positive effect on attitude toward using.
- (7) Perceived ease of use has significantly positive effect on perceived usefulness.
- (8) Perceived ease of use has significantly positive effect on behavioral intention to use.
- (9) Perceived usefulness has significantly positive effect on attitude toward using.
- (10) Perceived usefulness has significantly positive effect on behavioral intention to use.

Learning through the use of an IoT module was more effective than some other activities at supporting a higher cognitive presence. Three variables identified as significant factors in TAM (*Perceived usefulness*, *Perceived ease of use* and *Attitude toward use*) were shown to have a significant influence on the intention of learners to use the IoT module. Our findings that TAM can be used to predict *Behavioral intention to use* are in alignment with the findings of previous studies [28, 29].

Perceived usefulness had indirect as well as direct effects on learner's acceptance of the proposed module and *Attitude toward use* had direct effects. Some researchers have obtained similar findings [30–32].

6.1 Limitations

In spite of the significant findings of this study, it suffers from some limitations which may be subject to further research. The first weakness is that the sample was from one technical high school.

Although it was sufficient to represent the population, recruiting samples from several technical high school and using random sampling approach can improve the generalisability of the findings. The other limitation is that the overall results of the proposed model may indicate a need for further research in order to integrate more variables.

6.2 Suggestions

The following suggestions are made according to the teaching contents, teaching equipment, and test objects:

- (1) In future studies, test samples can be expanded, elementary and secondary school students can be taken as the test objects, and TAM can be further imported, in order to explore the behavioral intention to use and efficiencies of students applying IoT teaching module to relevant courses.
- (2) IoT module shall be connected to WiFi for teaching, thus, various problems, such as connection errors or failure of application coding, are likely to occur whenever the network signals are unstable. It is suggested to optimize the programming software to reduce network connection problems and improve the teaching fluency.

7. Conclusions

The purposes of this study were to explore students' acceptance of applying internet of things in a smart agriculture course. The students at a technical high

school were taken as the objects, and IoT teaching module was used as a learning medium to make the teaching activities more lively and smooth. The results of our statistical analysis demonstrate that the students in this study were willing to use the IoT module.

Students are highly satisfied with the IoT smart agriculture course. Observations during this study and the analysis report of the study questionnaire shows that most learners had positive evaluations on perceived enjoyment, perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention to use the IoT module, and most students agreed that the IoT smart agriculture course was helpful to them and could improve their learning outcomes.

This study analyzed the adoption of IoT module by technical high school students, which resulted in findings. First, ease of use is the primary factor that must be taken into consideration in the design of IoT module, followed by usefulness. Likewise, perceived usefulness may be able to predict attitude toward using. Second, path analysis demonstrated that the acceptance of the proposed module was directly influenced by attitude toward using, perceived usefulness, and perceived ease of use. Thus, ease of use should be a priority in the design of an IoT module. When designing an IoT module for technical high school students, teachers should pay attention to enriching learning content and ease of use, in order to improve the behavioral intentions of students.

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Wen-Jye Shyr is a professor at the Department of Industrial Education and Technology at National Changhua University of Education, Taiwan. His current research is in the mechatronics, graphical human computer interaction, sensors, energy education and engineering education.

Chin-Chung Huang and Chia-Hung Chen are doctoral students at the Department of Industrial Education and Technology, National Changhua University of Education, Changhua Taiwan, R.O.C.

Jhih-Syuan Wei is a master of Department of Industrial Education and Technology, National Changhua University of Education, Changhua Taiwan, R.O.C.