International Food and Agribusiness Management Review
Volume 23, Issue 2, 2020;; DOI: 10.22434/IFAMR2019.0121

Received: 31 July 2019 / Accepted: 13 November 2019

Implementation of Internet of Things depends on intention: young farmers' willingness to accept innovative technology

RESEARCH ARTICLE

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Abstract

Innovative applications of smart technology constitute a current trend in agricultural development. This study employed a technology acceptance model to explore the intention of young farmers to apply Internet of Things systems in field-level management of Taiwanese farms. An online questionnaire was used to collect data regarding farmers aged 45 years or younger who were currently engaged in agricultural production. Statistical analysis of 241 valid questionnaires revealed that young farmers' intention to use innovative technologies was affected mainly by perceived organizational support, followed by average annual turnover, perceived usefulness, perceived ease of use, and sense of trust in the system supplier. This study suggests that agricultural administration agencies should consider farmers' farming needs and intention to use; agencies should employ problem-solving and design thinking when developing smart agriculture policies. Insightful design of incentives and guidance measures enables young farmers to maximize achievement and to minimize effort.

Keywords: Internet of Things, smart agriculture, technology acceptance model, technological innovation, young farmer
JEL code: O33, Q16

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1. Introduction

From the perspective of demographic transition, Taiwan is facing a critical moment of alternation of generations and rural transformation. Taking the needs and changes of agricultural workforce as an example, the number of agricultural workers in Taiwan has declined substantially from 1.065 million in 1992 to the current 557,000 accounting for only 4.91% of the total employed population; 75% of these agricultural workers were pluriactive. In addition, the average age of the typical agricultural worker in Taiwan has reached 63.2 years, which is higher than the average ages of workers in other industries (Council of Agriculture, 2018). Labor shortages and aging are currently the greatest difficulties faced by Taiwan's agriculture industry (Chen *et al.*, 2016a).

Because Taiwan must stabilize its agriculture industry and achieve sustainable development, Taiwan must encourage young people to devote their lives to agricultural production and must employ technological innovation to produce competitive professional farmers. Among various domestic agricultural policies, the Smart Agriculture 4.0 Program planned and introduced by the Council of Agriculture was a crucial policy that aimed to solve the problem of labor shortages in rural areas and to raise production efficiency to a globally competitive level (Chen *et al.*, 2016b; Council of Agriculture, 2016; Kaloxylos *et al.*, 2012; Roopaei *et al.,* 2017; Wolfert *et al.*, 2017). Through the practice of interdisciplinary collaboration, the government aims to help solve the crises of a continually ageing agricultural labor force and a gap in passing down farming knowledge.

The Smart Agriculture 4.0 Program features the integration of innovative technologies (e.g. sensing devices, smart facilities, Internet of Things (IoT) and Big Data analytics) into the field of agriculture. The program's guidance in application of smart production and smart management helps solve the predicament of farmers working alone (Council of Agriculture, 2016; Kitchen, 2008; Soltani-Fesaghandis and Pooya, 2018). Smart agriculture, most characterized by precision agriculture, incorporates diverse expertise, skills, hardware components, and analytical software into agricultural production and business management while taking into account the passing down of traditional farming and techniques (Lamb *et al.*, 2008; Vellidis *et al.*, 2008).

However, farmers' intention to accept new concepts and employ innovative technology is mainly determined by whether the system is practicable, easy to use, and affordable (Legris *et al.*, 2003; Wang *et al.*, 2006). Literature has indicated that not all beginning farmers chose to adopt smart agriculture as their business model; conversely, some existing farmers are eager to surpass the traditional operational frameworks of producing agricultural commodities (Pivoto *et al.*, 2018; Mark *et al.*, 2016). The intention of domestic farmers to adopt innovative technologies affects the outcome of smart agriculture policy promotion, but relevant studies are rare (Protopop and Shanoyan, 2016), indicating a theoretical gap that requires narrowing. Therefore, researchers of this study were motivated to conduct an in-depth investigation into this topic.

The present study referenced the system developed by the Council of Agriculture to facilitate the engagement of young adults in agriculture and provide guidance to young farmers regarding business innovation. Accordingly, this study proposes two research questions: which factors would affect the intention of young farmers to accept IoT? How would these factors affect the intention of young farmers to accept IoT? The obtained results may serve as valuable references for the relevant central and local government agencies to formulate polices regarding young farmer guidance and promote relevant measures. Moreover, the results can help information and communications technology operators in terms of planning and actual practice of strategies for smart agriculture promotion.

2. Literature review

2.1 Smart agriculture and Internet of Things applications

Taiwan's Smart Agriculture 4.0 Program was undertaken by domestic agriculture administration agencies for promotion of smart agriculture (Council of Agriculture, 2016). Taking the characteristics of domestic agriculture development into account, said program aimed to assist smallholder farmers in facing the challenges of an ageing population, labor shortages, and extreme weather. In terms of production management, precision agriculture, which first emerged in the 1980s, is considered to be the origin of smart agricultural production. Precision agriculture is characterized by its potential to improve resource utilization, increase profits, and reduce the impact of agricultural production on the environment (Paustian and Theuvsen, 2017). Therefore, precision agriculture was defined as a management strategy that uses information technology to obtain data from multiple sources to support crop production decisions (Lamb *et al.*, 2008; Mazon-Olivo *et al.*, 2018).

The main technologies involved in Smart Agriculture 4.0 Program are remote sensing technology, global positioning systems, geographic information systems, expert systems, intelligent decision support systems, and Big Data analytics (Li and Chung, 2015; Vellidis *et al.*, 2008). In practice, the use of field server and wireless sensing network technology can assist producers in understanding more efficiently the crop growth and field conditions; moreover, the problems encountered during agricultural production can be solved by expert systems in a timely manner (Bir *et al.*, 2018; Kitchen, 2008). At present, the application of Big Data analytics in agriculture is another essential area of development for smart agriculture (Sonka, 2014; Sykuta, 2016). Consumers regard the integration of e-commerce with IoT as a possible business opportunity because of the advantages of timely and transparent information. In addition to improving the efficiency of producers, IoT is applicable to establishment of traceability, risk management, and cold chain logistics technology for agricultural production and marketing. The combination of IoT technology and wearable technology may contribute to an innovative purchasing model for agricultural products (Goap *et al.*, 2018; Mazon-Olivo *et al.*, 2018).

Regarding agricultural production management, another advantage of incorporating IoT is minimization of manual operations (e.g. the complexity and potential risk of traceability paperwork). This proves that IoT has breakthrough application value in strengthening the safety management of agricultural products from the place of origin to the table and establishing consumers' confidence in domestic agriculture products (Goap *et al.*, 2018; Long *et al.*, 2017). In addition, in the rural regeneration plan promoted by the Council of Agriculture, the future vision of a smart-technology-based rural area involves the use of smart Internet technology to integrate the upper, middle, and lower tiers of the industry chain, thereby achieving a holistic action plan fulfilling the idea of 'from place of origin to the table.' The action plan mobilizes rural areas; that is, information technology support and interdisciplinary assistance reduce construction costs and enable traditional agriculture to create new value chains as well as establish new business connections and interpersonal interactions (Devaux *et al.*, 2018).

2.2 Technology acceptance model in agriculture industry

The effectiveness of smart agriculture policy promotion is determined by farmers' levels of understanding, acceptance, and application of innovative technologies (Bir *et al.*, 2018; Lamb *et al.*, 2008). The technology acceptance model (TAM) proposed by Davis in 1989 alleges that the attitude towards using, intention to use, and adopted behaviors of innovative technology are affected by users' perceived usefulness and perceived ease of use. This theory has become one of the most widely applied theories in both industry and academia. Recent studies have pointed out that the application of TAM enables acquisition of effective information regarding stimulating farmers' demand for innovative technologies and enhancing their positive attitude and intention to use (Paustian and Theuvsen, 2017; Tubtiang and Pipatpanuvittaya, 2015).

TAM suggests user acceptance and usage of an innovative technology is determined by two essential components: perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness refers to whether the application of innovative technology is conducive to solving intractable problems in the field, while perceived ease of use reflects the friendliness with which user interfaces and tool functions are presented. The friendliness of usefulness and ease of use reduces the cost for users to change their habits when they adapt by learning the new technology. Previous studies have proven that perceived usefulness and perceived ease of use affect each other in innovative technology acceptance. When individuals encounter an effective and user-friendly innovative technology, they have a high chance of employing the technology (Flett *et al.*, 2004; Kamrath *et al.*, 2018).

In addition, each user's category and situation also constitute external variables (Burton-Jones and Hubona, 2006; Shin, 2007; Turel *et al.*, 2007; Wang *et al.*, 2006; Yoon and Kim, 2007). For example, the current study considered smart agriculture with the objective of exploring the scale of smallholder production and their average economic standard (Kabbiri *et al.*, 2018). In addition, self-efficacy regarding technology, sense of trust, and perceived convenience are also critical factors to affect farmers to adopt computer systems (Amin and Li, 2014; Ta and Prybutok, 2016; Tubtiang and Pipatpanuvittaya, 2015). Regarding situated environment, analysis of external environments can be conducive to the quality of products and services as well as supply procedures, shipping services, reasonable prices, and appropriate promotion strategies all affect users' intention and enhance their perceptions of decision-making with innovative technology (Alambaigi and Ahangari, 2015; Amin and Li, 2014; Kabbiri *et al.*, 2018; Ta and Prybutok, 2016; Tsai *et al.*, 2014).

Accordingly, this study modified the basic pattern of TAM by focusing on perceived usefulness, perceived ease of use, external variables and behavioral intentions. We employed the scale of agricultural land, average annual turnover, product price and organizational support as external variables in addition to feelings of self-efficacy regarding computers, sense of trust and perceived convenience. Based on the aforementioned considerations, this study developed the following three hypotheses and a research framework as indicated in Figure 1.

H1: both perceived ease of use and usefulness affect young farmers' intention to accept IoT technologies.

H2: demographic variables (i.e. sex, age, educational attainment, years of agricultural experience, and primary crop type) affect young farmers' intention to accept IoT technologies.

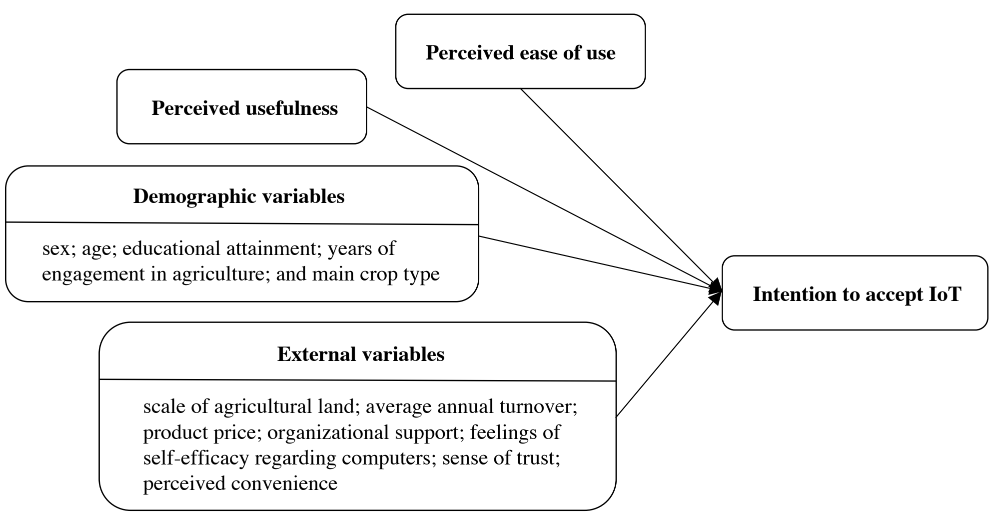

Figure 1. Research framework for exploring young farmers' intentions to accept Internet of Things.

H3: the level of young farmers' intention to accept IoT technologies differs depending on external variables (scale of agricultural land, average annual turnover, product price, organizational support, feelings of self-efficacy regarding computers, sense of trust, and perceived convenience).

3. Methods

3.1 Research samples

This study aimed to determine the intention of domestic farmers to adopt innovative technologies, particularly that of young farmers toward smart agriculture currently promoted by agricultural administration agencies. By applying IoT smart sensor technology to field-level production management, this study analyzed the factors affecting the intention of Taiwan's young farmers to integrate IoT tools into agricultural production. This study selected young farmers (aged 45 years or younger) who were currently engaged in agricultural production as participants. The investigation process involved the administration of an online questionnaire to members of young farmers' associations.

3.2 Research instruments

This questionnaire contained five subscales. Demographic variables, the usefulness of innovative technology in agricultural production (perceived usefulness), the ease of applying innovative technology in agricultural production (perceived ease of use), and other external variables affecting farmers' acceptance of innovative technology were presented respectively in the first, second, third and fourth subscales of the questionnaire. More details of each construct are presented as follows:

- Demographic variables: this subscale contains basic information such as sex, age, educational attainment, years of engagement in agriculture, and main crop type.
- Perceived usefulness: based on the suggestions of Davis (1989), Flett *et al.* (2004), and Kamrath *et al.* (2018), this subscale examines participants' opinions on whether the application of IoT-based smart sensor technology facilitates the management of agricultural production; this subscale has a total of four items.
- Perceived ease of use: referencing the findings of literature (Davis, 1989; Flett *et al.*, 2004; Kamrath *et al.*, 2018) this subscale examines participants' opinions on the user-friendliness of IoT-based smart sensor technology; this subscale has a total of four items.
- External variables: following the suggestions that have been published in previous articles (Alambaigi and Ahangari, 2015; Amin and Li, 2014; Kabbiri *et al.*, 2018; Tsai *et al.*, 2014; Tubtiang and Pipatpanuvittaya, 2015), this study covered key external variables, namely self-efficacy regarding computers, perceived convenience, sense of trust, area of arable land, annual turnover, product price, and organizational support.
- Intention to accept IoT: based on the suggestions of Davis (1989) and Kamrath *et al.* (2018), this subscale examines participants' intention to accept IoT; this subscale has a total of four items. This is the dependent variable which is continuous.

The questionnaire is composed of single-response questions, with a 6-point scale (1 = strongly disagree; 2 = disagree; 3 = slightly disagree; 4 = partly agree; 5 = agree; 6 = strongly agree) employed as the evaluation method based on the suggestions of quantitative researchers (Grant *et al.*, 2017: 35). Missing answers to survey questions were deemed as missing data. The questionnaire conforms to international scale standards and was repeatedly verified to ensure that each questionnaire item is highly reliable and valid.

3.3 Research process

Data collection was conducted using online questionnaire on the SurveyCake survey platform (https://www.surveycake.com/tw/). We promoted the questionnaire through personal channels and domestic young farmer organizations in various regions of the country (e.g. LINE groups of young farmers' associations, agricultural promotion classes, farmer's associations) to enhance participation. To meet ethical considerations, this study clearly informed the respondents of the research objective and their rights on the front page of online questionnaire.

Moreover, this study clearly stated that the data would be anonymized for subsequent data analysis to reassure respondents of the safety of their privacy. SPSS version 21 for Windows (SPSS, IBM, Armonk, NY, USA) was employed for statistical analysis of the obtained data. Demographic variables of the investigated young farmers were described using descriptive analysis; variance and multiple regression analyses were conducted to other constructs. Through the aforementioned steps, this study was able to explore the intention of Taiwan's young farmers to employ smart sensor technology of the IoT and the factors affecting their decisions.

4. Data analysis

4.1 Descriptive statistics

Table 1 reveals that the majority of participants were men (76.3%), with an educational attainment of university or junior college (54.4%). For the scale of agricultural land, 1.44-2.40 acres was the most common among all scales for both self-owned and rented arable land (36.1%; 28.6%). Regarding the majority crop type, fruits occupied the most land (28.2%), followed by tea (19.9%) and vegetables (13.3%). Approximately 41.9% of the respondents had an average annual turnover of NT$ 700,000-1,800,000 with an average age of 36.4 years, and an average of 7.9 years of engagement in agriculture.

4.2 Factor analysis

This study conducted factor analysis for each subscale. As expected, each construct was represented by a single factor from the yielded results. The four items in the perceived usefulness subscale received factor loadings of 0.92-0.95, means of 4.83-4.95, standard deviations (SDs) of 0.98-1.09, and a Cronbach's α-value of 0.95; moreover, the percentage of variance explained was 86.16%, indicating superior reliability and validity. The four items in the perceived ease of use subscale received factor loadings of 0.86-0.93, means of 4.37-4.76, SDs of 1.13-1.22, and a Cronbach's α-value of 0.92; the proportion of variance explained was 79.79%, indicating great reliability and validity. The two items in the self-efficacy subscale all received a factor loading of 0.95, a mean of 4.8, SDs of 1.03-1.05, and a Cronbach's α-value of 0.88; the obtained percentage of variance explained was 89.59%, implying satisfying reliability and validity. The two items in the sense of trust subscale both received a factor loading of 0.93, means ranging between 4.68 and 4.75, SDs of 0.95-0.97, and a Cronbach's α-value of 0.85; the percentage of variance explained was 87.09%, signifying superior reliability and validity. The two items in the organizational support subscale both received a factor loading of 0.95, a mean of 4.44, SDs of 0.99-1.10, and a Cronbach's α-value of 0.89; the percentage of variance explained was 90.35%, indicating that the scale reliability and validity fulfilled the designated requirements. The three items in the perceived convenience subscale received factor loadings ranging between 0.96 and 0.97, means ranging between 4.81 and 4.93, SDs of 0.91-1.03, and a Cronbach's α-value of 0.96; the proportion of variance explained reached up to 92.56%, indicating superior reliability and validity. Finally, the four items in the intention to use subscale received factor loadings ranging between 0.90 and 0.94, means of 4.28-4.63, SDs ranging between 1.03 and 1.18, a Cronbach's α-value of 0.94; the percentage of variance explained was 84.16%, indicating favorable reliability and validity.

4.3 t-test and analysis of variance

The independent samples *t*-test results revealed that male and female farmers exhibited a significant difference in their intention to use IoT technology. On average, men had higher intention-to-use compared to women (Table 2).

Table 1. Descriptive statistics (n=241).

Demographic / operation type variable	Number (%)
Participants	
Man	184 (76.3%)
Woman	57 (23.7%)
Age[1]	mean: 36.4 SD: 5.8
Years of engagement in agriculture[1]	mean: 7.9 SD: 6.8
Educational attainment	
Junior high school or lower	12 (5.0%)
Senior or vocational high school	49 (20.3%)
University or junior college	131 (54.4%)
Graduate school or higher	49 (20.3%)
Area of self-owned arable land	
≤1.43 acres	43 (17.8%)
1.44-2.40 acres	87 (36.1%)
2.41-4.80 acres	51 (21.2%)
4.81-7.20 acres	38 (15.8%)
7.21-12.00 acres	7 (2.9%)
≥12.01 acres	15 (6.2%)
Area of rented arable land	
1.43 acres	80 (33.1%)
1.44-2.40 acres	69 (28.6%)
2.41-4.80 acres	31 (12.9%)
4.81-7.20 acres	24 (10.0%)
7.21-12.00 acres	11 (4.6%)
≥12.01 acres	26 (10.8%)
Majority crop type	
Wheat and rice	28 (11.6%)
Mixed cropping	21 (8.7%)
Vegetables	32 (13.3%)
Fruits	68 (28.2%)
Tea trees	48 (19.9%)
Mushrooms	2 (0.8%)
Flowers	19 (7.9%)
Others	23 (9.5%)
Average annual turnover	
≤NT$ 200,000	28 (11.6%)
NT$ 210,000-700,000	65 (27.0%)
NT$ 700,000-1,800,000	101 (41.9%)
≥NT$ 1,810,000	47 (19.5%)

[1] Number in year; SD = standard deviation.

Analysis of variance (ANOVA) results reveal that difference in crop type did not affect young farmers' intention to use IoT technology. The difference in willingness-to-pay for system implementation did affect intention-to-use; farmers who were willing to pay NT$ 60,000 and had a higher intention-to-use than did farmers willing to pay NT$ 10,000 or less. The variation in willingness-to-pay for information service (per month) also affected farmers' intention-to-use; farmers' willing to pay NT$ 300 per month had a higher intention-to-use than did those willing to pay NT$ 100 or less per month (Table 3).

Table 2. Independent *t*-test results of gender differences in variables (n=241).

Variable	Intention-to-use[1]				
	M	SD	*t*-test	*P*-value	df
Man	4.48	1.00	2.17	0.03	239
Woman	4.14	1.10			

[1] M = mean; SD = standaard deviation; df = degree of freedom.

Table 3. ANOVA of differences in variables according to willing-to-pay (n=241).[1]

Variable		Intention to use				
		M	SD	F	df	Scheffe's test
Willingness-to-pay for system implementation	a. ≤NT$ 10,000	3.98	1.06	5.31***	235	c, d, e, f > a
	b. NT$ 11,000-50,000	4.37	0.96			
	c. NT$ 51,000-100,000	4.78	0.81			
	d. NT$ 101,000-150,000	4.97	0.83			
	e. NT$ 151,000-200,000	4.81	1.04			
	f. ≥NT$ 201,000	4.64	1.23			
Willingness-to-pay for information service (per month)	a. ≤NT$ 100	4.02	1.17	7.14***	237	c, d > a
	b. NT$ 101-300	4.28	1.00			
	c. NT$ 301-500	4.78	0.85			
	d. ≥NT$ 501	4.67	0.88			

[1] Significant at ****P*<0.001; M = mean; SD = standaard deviation; df = degree of freedom.

4.4 Multiple regression analysis

The regression analysis result indicated that the explanatory power of this regression model reached 70% (R^2=0.70). Aside from self-efficacy regarding computers, perceived convenience, self-owned arable land, rented arable land, willingness-to-pay for system implementation, and willingness-to-pay for information service (per month), other independent variables obtained significance values lower than 0.05, indicating that they exert significantly positive effects. Organizational support and average annual turnover are the two most critical factors affecting young farmers' decisions. Perceived usefulness, perceived ease of use, and sense of trust are also factors affecting young farmer's decision of adopting IoT. This result shows that strong organizational support, high income, and strong sense of trust as well as high perceived usefulness and high perceived ease of use towards IoT system positively affect farmers' intention to this technology. Conversely, regression analysis results indicated that factors of land ownership (area of self-owned or rented arable land) and the willingness-to-pay for system implementation did not affect young farmers' decisions regarding adopting IoT.

5. Discussion

5.1 Factors affecting young farmers' intention to use Internet of Things

Results from independent samples *t*-testing indicated that domestic young farmers' decisions regarding innovative technologies for smart agriculture varied with sex. In general, young male farmers had higher intention to apply IoT technology to field-level management and solving farming problems than did young female farmers, a result consistent with the literature (Doss and Morris, 2001; Ndiritu *et al.*, 2014). In addition, ANOVA also indicated that difference in willingness-to-pay for system implementation and information

Table 4. Multiple regression analysis on intention to accept the Internet of Things (n=241).

Variable		Intention to use		
		Beta	***t*-test**	***P*-value**[1]
Constant			-1.082	0.28
Perceived usefulness		0.199	2.962	0.003**
Perceived ease of use		0.160	2.464	0.014*
Self-efficacy regarding computers		-0.038	-0.757	0.45
Sense of trust		0.144	2.104	0.036*
Organizational support		0.265	4.747	0.000***
Perceived convenience		0.136	1.735	0.084
Area of self-owned arable land		-0.035	-0.842	0.401
Area of rented arable land		-0.018	-0.437	0.663
Average annual turnover		0.214	4.898	0.000***
Willingness-to-pay for system implementation		-0.031	-0.709	0.479
Willingness-to-pay for information service (per month)		0.008	0.194	0.846
Model summary	R^2	0.70		
	F	49.31		
	P-value	0.000***		

[1] Significant at $^{*}P<0.05$, $^{**}P<0.01$, $^{***}P<0.001$.

services affected the technology acceptance of young farmers. The results indicated that farmers willing to pay high prices for system implementation or information services (per month) had high intention-to-use.

Subsequently the regression analysis confirmed that the intention-to-use of young farmers was significantly affected by organizational support, average annual turnover, perceived usefulness, perceived ease of use, and sense of trust, among which organizational support was the factor that exerted the most positive effect in encouraging young farmers to accept IoT technology. This result is consistent with conclusions of some articles (Alambaigi and Ahangari, 2015; Kabbiri *et al.*, 2018; Kamrath *et al.*, 2018; Ta and Prybutok, 2016). The conclusion that young farmers who receive support from family and fellow farmers are relatively willing to employ IoT technology particularly reflects Taiwan's agricultural structure and the close relationships between agricultural affairs, family affairs, and community affairs; accordingly, these results can clarify the focus of IoT marketing. In addition, young farmers' associations with a high average annual turnover were relatively willing to employ IoT technology. This result reflects the fact that the adoption of innovative technologies is determined by economic strength; this adheres to the conclusion in the section regarding willingness-to-pay for system software and hardware.

The findings of this study also resonate with the TAM proposed by Davis (1989). For example, the intention of domestic young farmers to employ innovative technologies is subject to the effects of perceived usefulness and perceived ease of use. To stimulate the intention-to-use among young farmers, smart agriculture technology involving the use of IoT must effectively cater to pertinent problems in agricultural production, field-level management, and sales while retaining its user-friendliness. The literature also indicated that the reputation of system suppliers and users' trust in software and hardware suppliers affect users' intention to adopt innovative technologies (Alambaigi and Ahangari, 2015; Amin and Li, 2014). This study verified that young farmers' intention to adopt smart sensor technology increases with the reputation of IoT suppliers, the quality of field-level information analysis, and the security of individual privacy.

The results indicated that factors of land ownership (area of self-owned or rented arable land), willingness-to-pay for system software, self-efficacy regarding computers, and perceived convenience of IoT did not affect the young farmers' intention to adopt IoT innovation. This shows that the adoption of an innovative technology among young farmers is mainly determined by whether the innovative technology can effectively solve the problems they encounter in agricultural production and marketing, whether the software and hardware supplier is reliable, and whether the technology is prevalent among their peers.

5.2 Research limitations and future research

This study has identified the key factors affecting young farmers' intention to employ IoT, but has been subject to the following limitations as a prospective pilot study. First, application of IoT to field-level management is prevalent in other countries but still underdeveloped in Taiwan; that is, no well-developed system is available in Taiwan. This study only offered a simulated image as a reference for the participants to complete the questionnaire. This may have affected the young farmers' evaluation of their intention-to-use, rendering the results less precise. Future research is suggested to wait until the launch of a well-developed IoT system to reinvestigate its applicability or collaborate with the point of sale to perform Big Data analysis of consumer behaviors.

Compared with farmers in the past, young farmers are offered more opportunities to access innovative technologies and are more familiar with the trends of IoT applications in agriculture industry. However, young farmers are not the main labor force in agricultural production at present; the majority of them still rely on the financial support of agricultural administration agencies. As a result, results of this study were only preliminary responses reflecting the acceptance of IoT technology by young farmers. Because this study only focused on young farmers engaging in field crop production, future studies are advised to conduct such investigations five years later using a renewed questionnaire encompassing agriculture, forestry, fishery, and animal husbandry.

Finally, because the questionnaire was distributed online, timely assistance and explanation could not be provided to respondents who encountered problems answering questionnaire items; this may have affected the intention of young farmers to complete the questionnaire. In addition, multiple regression analysis could be overly simplistic for a causal study such as this one. Therefore, this study could only produce the statistical data mentioned in the previous section under a designated range of conditions. Future studies may adopt other types of quantitative research methods to surpass the limitation resulting from the research method employed in this study.

6. Conclusions, contributions and suggestions

In conclusion, domestic young farmers were mainly subject to the effect of organizational support, followed by the effects of average annual turnover, perceived usefulness, perceived ease of use, and sense of trust toward the technology supplier. The results also signified that young male farmers were more willing to accept IoT technology than were young female farmers. In addition, farmers with high values of willingness-to-pay for system implementation and subsequent information services had high intention to employ IoT system. To sum up the aforementioned research results, contributions and practical implications regarding policy establishment and industrial R&D for agricultural administration agencies, technology suppliers, and young farmers are detailed separately as follows.

Subject to a policy of supporting smallholder farmers and strengthening agricultural enterprises in Taiwan, our results support the urgent call for systematic investigation to determine the needs of young farmers running various businesses and the predicaments they encounter during actual agricultural operations. Based on such investigations, agricultural administration agencies can promote smart agriculture development to fulfil the diverse needs of agribusiness in Taiwan. In such conditions, the agencies may select crop types that have developmental potential or that require urgent transformation, after which a demonstration plan can be submitted for evaluation. According to the actual implementation in fields, plans yielding favorable outcomes may be gradually implemented for other crops to facilitate the structural transformation of the agriculture industry. Moreover, the agencies may integrate newly developed theories of sustainable development (e.g.

climate change adaptation and responses) into policy discourse to strengthen the development of smart agriculture and its related applications in Taiwan.

Our results also contribute to future IoT system development, which should focus on enriching prior knowledge for operations of agricultural production and field-level management as well as enhancing cross-disciplinary cooperation between Taiwan's information service department and agricultural department. Because young farmers' adoption of any innovative technology is determined mainly by that technology's perceived usefulness and ease of use, design expertise should be incorporated to provide an intuitive, user-friendly, and aesthetically pleasant IoT user interface. The content and operation of the smart agricultural application system must be designed in accordance with the habits and user experience of young farmers. Both agricultural administration agencies and system operators should adopt problem-solving and design for promoting smart agriculture, thereby reducing the noneconomic costs for users in adopting innovative technologies and achieving effective policy promotion with minimal effort.

Furthermore, our results contribute to effective promotion by determining that organizational support was the most crucial factor affecting IoT technology adoption by young farmers. This implies that both agricultural administration agencies and IoT operators should strengthen their links to existing farmers' organizations (e.g. farmer's associations, young farmers' associations, and agricultural promotion classes) with the core objective of promoting the application and transformation of smart agriculture. We propose a paradigm whereby young farmers adopt innovative technologies of smart agriculture. This paradigm can be established first by identifying the opinion leaders and the key individuals who adopted innovation early in their organizations' development and then by applying the preliminary plans of the aforementioned examples. This paradigm will facilitate the effective promotion of related policies and technology applications in the future.

Technology innovation has become an essential trend in the development of various industries. Compared with manufacturing and high-tech industries, agriculture industry typically pays more attention to the conditions of farm sites than to technology. The successful development and transformation of the agriculture industry require deep understanding of local social contexts and farmers' habits. In the 6th National Agricultural Congress of Taiwan held in 2018, the use of smart technology was presented as an imperative for adjusting the agriculture industry structure and comprehensively enhancing agricultural competitiveness. However, as stated in the title of this study – implementation of IoT depends on intention – the research, development, and application of any innovative technology should be human-oriented and should serve the development of civilization.

Acknowledgements

The authors acknowledge financial support from the COA (Grant No. 106AS-18.2.2-FS-#3,107AS-14.1.3-FS-#2). The results and their interpretation are those of the authors, and are not those of the Council of Agriculture in Taiwan.

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