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Manuscript title: Exploring Farmers' Knowledge, Attitude and Adoption of Smart Agriculture Technology in Taiwan

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Abstract

Climate change and food security are the most relevant issues to be considered in sustainable agricultural development. The FAO's initiative of climate-smart agriculture has attracted international attention. Since then, the smart agriculture (SA) has been recognized as the most influential trends in contributing to agricultural development. Therefore, encouraging farmers to adopt digital technologies and mobile devices into farming practices becomes a policy priority worldwide. However, there is limited literature available on psychologic factors that drive farmers' intentions to adopt SA technologies. The purpose of this study is to investigate how farmer's knowledge and attitude toward SA affects their adoption of smart technologies in Taiwan. A total of 321 farmers participated in the project's survey in 2017 and 2018, from which the data was used to perform an OLS regression model of SA adoption. This study contributes to a preliminary understanding of relationship between innovation and adoption of SA technologies in a small-scale farming economic context. The findings suggest that the policy makers and R&D institutes need to concentrate on improving market access for well-known and high important SA technologies.

Keywords: smart agriculture; agriculture 4.0; innovation adoption; digital technology; Taiwan

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INTRODUCTION

Climate change and food security are the most relevant issues to be considered in sustainable agricultural development, nowadays. The Food and Agriculture Organization of the United Nations (FAO) firstly proposed the climate-smart agriculture (CSA) concept which has attracted international attention for its innovative use of technology in addressing agricultural challenges [1,2]. The objectives of CSA are threefold, including sustainably increase food productivity, improve adaptive capacity of farming systems, and mitigate climate change where possible [3,4,5]. In addition to the climate change concerns, the smart agriculture (SA) is an emerging term which puts more emphasis on the role and application of innovative technology in the agricultural practices.

The SA strategy focuses on the use of digital technology to create percision farming technology solution, especially combined application of information and communication technologies (ICT) and other new interconnected equipment and techniques. The internet of things (IoT), drones, robots, big data, cloud computing and artificial intelligence are the good examples expected to be applied to novel farming practices [6]. Due to integration of precision farming system and digital technology, SA has been recognized as the most prevalent trend in agricultural development which may contribute to fewer inputs, higher yields and less damage of agricultural production. Nowadays, the digitized agriculture becomes a mainstream trend in many countries [7].

There are several similar but inconclusive concepts were used in different research areas, such as agriculture 4.0, precision agriculture, smart farming, digital agriculture, virtual agriculture, big-data in agriculture, IoT in agriculture, and interconnected agriculture [8,9]. Although, those emerging concepts exist slight differences and emphasis on specific technological applications. Most of them shares common traits and values which brings new and intelligent technologies into farming practice and introduces a resource efficient approach for farmers to minimizing production costs, reducing farming risk or increasing productivity [10]. According to inventory of the European smart agricultural knowledge and innovation systems (Smart-AKIS) program, the SA is mainly related to three inter-connectable new technology categories which contains the farm management information systems, precision farming, and agricultural automation. For instance, the smart phone application software has been extensively used in remote monitoring and controlling farming equipment. Similar example can be found in the plant factory which has taken advantage of IoT, big data, sensing and monitoring techniques and automatic environmental control system [7]. Therefore, not only the agribusiness but also small-scale farmers can benefit from application of new technology.

Taiwan agricultural sector is characterized by small-scale holdings and identified as a global disaster hotspot, such as typhoons and floods [11]. Complying with the Industry 4.0 development and climate change risk, the Agriculture 4.0 Project was launched by Council of Agriculture (COA) of Taiwan in 2017. This pilot project attempts to introduce advanced technologies like intelligent devices, sensing techniques, robot, IoT and big data analysis to agricultural productivity. Taiwan government has invested about NT$ 4.5 billion towards upgrading agricultural technologies, and renamed as the Smart Agriculture Project in 2018. The SA Project aims at overcoming the restrictions of natural resource and shortages in manpower, then to facilitate intelligent production and digital marketing of agricultural business [12]. The principal strategies of the SA Project are three-fold. Firstly, the COA has selected ten pilot agri-businesses as the prioritized targets for the first stage of promotion SA, including moth orchid, seedling, mushroom, rice, agricultural facility, aquaculture, poultry, traceable agricultural products, dairy, and offshore fishery. Secondly, the agricultural R&D institute takes advantage of cross-domain technological innovation to create digital agri-services, value chain and new communication models between producers and consumers, such as IoT-based environmental control modules, labor saving carrying equipment, marketing management information platform. Considering training smart farmers is the foundation of SA development, the last but not the least strategy is to cultivate the next generation farmers to meet the needs of smart agricultural development [13,14].

Given that human resource development is a key factor for developing SA, how to encourage farmers and agri-businesses adopting innovative digital technologies and intelligent mobile devices into farming practices is becoming a policy priority in Taiwan. Therefore, the COA and National Taiwan University have collaborated to develop and design a series of SA training programs for fostering the human resources of the smart agriculture. The educational objective of the SA training programs focuses on enhancing trainees' knowledge, attitude and practical competences about the smart agriculture. There are four types of training courses offered, including, indoor lecture of SA general education, on-site visiting and training, international visits and exchanges, and setting up SA service teams for each pilot SA industry which provides individual tailor-made technical assistance [14]. However, there is limited literature available on psychologic factors and individual characteristics that drive farmers' intentions to adopt SA technologies. Consequently, the purpose of this study is to investigate the association among SA knowledge, attitude and adoption behavior. Moreover, we further address how farmer's knowledge and attitude of smart agriculture affects their adoption of SA technologies in Taiwan.

The research problems of this study will address the following questions regarding knowledge, attitude and adoption in relation to SA technology. For example, What types of SA technology are important for farming practices and better understood by farmers? What are the driving factors for SA adoption behaviors? To what extent the socio-demographic variables, knowledge and attitude may be associated with the adoption of SA technologies. Previous studies have focused on the role of psychological factors within the individual behaviors, such as social learning theory, theory of reasoned action, theory of planned behavior [15,16]. Few studies in agriculture have identified associations between farming practices and attitudes and other psychological determinants [17,10]. In addition, the theory of planned behavior has been applied and tested in various fields extensively, since it is an extension of the theory of reasoned action [18]. Furthermore, theory of planned behavior identifies hierarchical relations among various beliefs and attitudes toward behavior. Due to the educational goals of an agricultural training program is multi-faceted, including to improve the target group's knowledge level, as well as to change attitudes, and adoption behaviors [19,10]. Our study applies a comprehensive knowledge-attitude-practice model (KAP) based on previous literature, to further investigate the relationships of the participants' KAP of the SA training course. Based on the KAP model, we hypothesize that SA knowledge and perceived importance has a positive correlation between each other. Moreover, both of the SA knowledge and importance perception have positive effect on adoption of smart agricultural technologies.

DATA AND MEASURES

Data used in this study were drawn from a self-conducted survey in the summer of 2017 and 2018. The research subjects were trainees of the SA training program which sponsored by the COA in Taiwan. All the participants were asked to fill out the questionnaire as a reference for training courses planning, through a way of face-to-face interview. The sample characteristics are presented in Table 1. Among 321 respondents, of which 79.1% were male, with average

age of 42.61 years old, 15.3% and 58.6% of them graduated from senior high school or below and college, respectively. In addition, the farming feature shows that 12.8%, 22.7% and 64.5% of respondents were principal operators, hired staffs of agribusiness, and self-employed farmers, respectively. The average farm size was 3.9 hectare, the annual turnover accounted for 25.9%, 28.3%, 26.8% and 19.0% for NT$ 0.2 million or below, 0.2-1 million, 1-5 million, and 5 million or above, respectively.

Table 1. Descriptive statistics of sample characteristics (n=321)

Variables		Frequency (Mean)	% (SD)
Gender	Male	254	79.1
	Female	67	20.9
Age (years)		42.61	11.22
Edu level	Senior high or below	49	15.3
	College/University	188	58.6
	Graduated or above	84	26.2
Farmer type	Owner or operator of Agribusiness	41	12.8
	Hired staffs in Agribusiness	73	22.7
	Self-employed	207	64.5
Farm size (hectare)		3.92	13.57
Annual turnover (NT$)	0.2 million or below	83	25.9
	0.2-1 million	91	28.3
	1-5 million	86	26.8
	5 million or above	61	19.0

Given that the main purpose of this study is to explore the knowledge, attitude and practices of smart agriculture. The questionnaire design has referenced previous researches as discussed in the literature section. The dependent variable is the SA adoption which refers to the self-reported adoption level of SA technology in their farming practices. To ensure reliability and validity of measurements of the dependent variable, the most common SA technologies photographs were presented in the interview. In doing so, the respondents were able to rate the adoption level of the SA technology scores from 0 (the lowest adoption) to 100 (the highest adoption).

The principal independent variables in this study is the level of knowledge and perceived importance of each type of SA technology. According to the smart-AKIS's inventory of SA technologies [7], there are several farming facilities and equipment with smart technology has been developed in Taiwan, including IoT, wireless sensing, monitoring with automated climate data acquisition (climate sensing & monitoring), biological image detection and recognition (image recognition), cloud service and big data analysis (big data), mobile phone apps for farm management (apps), robotic farming machine (robotic), drones spraying and aerial photography (drones), automatic environmental control system (automatic system). In the survey, eight types of SA technologies were asked to evaluate respondents' knowledge level. Reference answers include: "Never heard (= 1)", "Heard but do not know much", "Got a general understanding", "Well understand and can explain it to others (= 4)". In addition, we used the same indicators to measure respondents' importance level in relation to adopting SA technology. Level of SA importance was measured by the question: "To what extent do you think about the importance of this SA technology for improving your farm business management?" All questionnaires were made use of a 4-point Likert's scale, with a larger value of the score indicating a higher degree of knowledge and importance about the SA technology, respectively (such as, 1=not important at all to 4=very important).

The socio-demographic variables included: gender (male=1), age (in years), education level (e.g. three dummy variables of senior high school or below, college or university, and graduated or higher), farmer's type (e.g. three dummy variables of agribusiness operator, hired staffs, or self-employed farmer). Moreover, farm features contained farm size (in hectare), and average annual turnover (e.g. four dummy variables of NT$ 0.2 or below, 0.2-1, 1-5, and 5 million or above).

Statistical analysis

The primary purpose of this study is to explain how psychological factors affect the adoption behavior of SA technology, while controlling for individual socio-demographic and farm characteristics. The empirical analysis is conducted in two steps. Firstly, this study explored the association between farmers' knowledge, perceived importance, socio-demographic characteristics, and adoption behavior of SA technology. The second stage analysis focuses on investigating how the exogenous determinants affects farmers' behavior of adopting SA technology. The following equation is the SA adoption function, which examines the relationship between SA adoption level and SA knowledge, SA importance, as well as socio-

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demographic and farm characteristics. The corresponding ordinary least squares (OLS) regression equation is specified as follows.

$$SA\_Adoption_i = \alpha_0 + \beta\,\acute{}\,Knowl_i + \gamma\,\acute{}\,Imp_i + \lambda\,\acute{}\,Z_i + \nu\,\acute{}\,R_i + \varepsilon_i \quad (1)$$

where *SA_Adoption*$_i$ is the individual *i*'s self-reported score *related to SA adoption behavior*; *Knowl*$_i$ is the SA knowledge score for the individual *i*; *Imp*$_i$ is the SA importance score for the individual *i*; Z_i is a set of socio-demographic characteristics; R_i presents a set of farming features. The random error term ε_i is assumed to be normally distributed. α_0, β', γ', λ', ν' are the coefficients to be estimated. Of particular interest is β' and γ' which measures how the SA knowledge and importance level affects the SA adoption. All analyses were conducted using the SPSS software version 22.0 (SPSS Inc., Chicago, IL, USA).

RESULTS AND DISCUSSION

Association between SA knowledge, importance and adoption

The descriptive statistics of knowledge, importance and adoption level of the SA technologies were shown in Table 2. On average, the respondents self-reported score of SA adoption was 40.22 which corresponds with farming mechanization by using combustion engine or electricity. The total SA importance score was 25.87. Among all individual SA items, the top three important SA technologies, in order, were automatic environmental control system (3.24), farm management app (3.35), and cloud service and big data analysis (3.33). These results might reflect the fact that the automatic environmental control system and farm management app are evaluated as the most familiar and important smart technologies by respondents. Moreover, the total knowledge score accounted for 22.45. Among the interviewed SA technologies, the top three well-known new technologies, in order, were automatic environmental control system (3.04), drones spraying and aerial photography (2.93), and farm management app (2.90).

Table 2. Descriptive statistics of SA knowledge, importance and adoption (n=321)

SA Technology	SA Importance			SA Knowledge		
	Mean	S.D	Rank	Mean	S.D	Rank
Total adoption score	40.22	20.82	-	-	-	-
Automatic control system	3.24	0.74	1	3.04	0.81	1
Apps	3.35	0.57	2	2.90	0.96	3
Big data	3.33	0.59	3	2.68	0.94	7

IoT	3.27	0.52	4	2.75	0.81	5
Image recognition	3.23	0.58	5	2.59	0.97	8
Sensing & monitoring	3.22	0.57	6	2.71	0.93	6
Robotic	3.12	0.63	7	2.85	0.83	4
Drones	3.10	0.65	8	2.93	0.84	2

This study further investigates correlations among different indictors of SA knowledge, attitudes and practices. It is evident that significantly positive associations exist between all the KAP indicators. Table 3 and 4 showed the means, standard deviations, and correlation coefficients between individual SA technologies. The results of correlation among SA knowledge and adoption behavior are presented in Table 3. The individual coefficients are between .582 and .738. All the SA knowledge indicators were significantly and positively correlated to each other, as expected. The knowledge level of individual SA technologies are also significantly correlated with SA adoption. The top three highest correlation coefficients, in order, were farm management apps (r = .306), cloud service and big data analysis (r = .296), and biological image detection and recognition technique (r = .286), respectively. The results of correlation matrix supports the hypothesis that there exists a positive relationship among SA knowledge and SA adoption behavior, which are consistent with the findings of main studies in the field of innovation adoption [2].

Table 3. Correlation matrix of the SA knowledge and adoption (n=321)

SA Knowledge	1	2	3	4	5	6	7	8	9
1.IoT	1								
2.Climate sensing & monitoring	.644**	1							
3.Image recognition	.590**	.722**	1						
4.Big data	.666**	.712**	.762**	1					
5.APP	.638**	.657**	.691**	.717**	1				
6.Robtic	.583**	.610**	.582**	.632**	.610**	1			
7.Drones	.600**	.568**	.632**	.649**	.667**	.662**	1		
8.Automatic system	.597**	.602**	.638**	.695**	.645**	.645**	.738**	1	
9.SA adoption score	.251**	.219**	.286**	.296**	.306**	.249**	.224**	.270**	1

Note: ** stands for the significance level of p-value < .01.

The similar results were found in the correlation matrix of the SA importance and adoption behavior. Table 4 shows the correlation coefficients among the SA importance variables, which ranged from .319 to .667. As expected, all the SA importance indicators were positively correlated to each other significantly. Although most of the SA importance variables had significant correlation with SA adoption. However, the correlation coefficients of the SA importance variables and SA adoption were relative lower, compared with the SA knowledge counterparts. The highest coefficients only accounted for .266 for the automatic environmental control system. In addition, our results did not find significant relationship between the SA adoption and importance level of image recognition technique and drones technology. Because the correlation of some SA technologies was non-significant, the SA importance hypotheses of SA adoption were partially supported.

Table 4. Correlation matrix of the SA importance and adoption (n=321)

SA Importance	1	2	3	4	5	6	7	8	9
1.IoT	1								
2.Climate sensing & monitoring	$.458^{**}$	1							
3.Image recognition	$.320^{**}$	$.571^{**}$	1						
4.Big data	$.537^{**}$	$.509^{**}$	$.505^{**}$	1					
5.APP	$.442^{**}$	$.589^{**}$	$.556^{**}$	$.667^{**}$	1				
6.Robtic	$.367^{**}$	$.385^{**}$	$.422^{**}$	$.436^{**}$	$.470^{**}$	1			
7.Drones	$.319^{**}$	$.344^{**}$	$.488^{**}$	$.418^{**}$	$.402^{**}$	$.530^{**}$	1		
8.Automatic system	$.481^{**}$	$.383^{**}$	$.375^{**}$	$.524^{**}$	$.426^{**}$	$.355^{**}$	$.407^{**}$	1	
9.SA adoption score	$.129^{*}$	$.166^{**}$	0.016	$.132^{*}$	$.184^{**}$	$.148^{**}$	0.106	$.266^{**}$	1

Note: **, * stands for the significance level of p-value < .01 and <.05, respectively.

Effects of SA knowledge and importance on SA adoption

The estimated results of OLS multiple regression model of SA adoption are reported in Table 5. We begin our discussion of the results by looking at the findings of statistical tests. The adjusted R-square statistic indicates 25.3% of variation is explained by this regression model out of the total variation. Moreover, the F-value (10.02) of the overall significance test is less than the significance level of 0.001. These results show that the knowledge and importance of SA technologies, socio-demographic and farm management characteristics have a significant influence on the SA adoption.

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As exhibited in Table 5, the SA knowledge and importance level were found to be positively related to the SA adoption. For instance, a 1 percentage point increase in SA knowledge level significantly will result increase in SA adoption score by 0.932 percentage points among the respondents. Similarly, a 1 percentage point increase in SA importance level will result significant increase in SA adoption level by 0.811 percentage points. This result implies that for the participants in the SA training program have higher level of SA knowledge and importance are able to adopt innovative technologies into their farming practices. This finding is also consistent with previous studies [20] which supported having knowledge or perception of the SA technologies is an important determinant of innovation adoption behavior.

Although it is not the primary focus of this study, we briefly discuss the relationships between other determinants and the SA adoption behavior. The farming characteristics significantly affect the adoption level of the SA technologies. For example, those who work in the agribusiness showed high adoption level of the SA technologies than self-employed farmers, as expected [21]. In addition, the farm size is positively associated with the SA adoption. The annual turnover of farm also matters. Results indicate that larger farm size and higher annual turnover leads to higher level of the SA adoption. This finding implies that the farmers have larger farm scale or volume of business, it may enhance their investment decision to adopt the SA technologies into farming practices. This argument is in agreement with previous studies [10,22,23], the farm size and revenue are positively related with innovation adoption. However, the socio-demographic characteristics were not significantly associated with the SA adoption, except age. The results showed that the respondent's age and SA adoption was positively correlated.

Table 5. Estimation results of the OLS regression (Dependent variable: SA adoption, n=321)

Variable	Coefficient	s.e.	t-value
Total_Knowledge	0.93 ***	1.50	4.97
Total_Importance	0.81 **	2.54	2.56
Socio-demographic characteristics			
Male	3.66	2.52	1.45
Age	0.23 **	0.10	2.42
University	2.65	2.95	0.90
Graduated or above	-0.26	3.35	-0.08

Farming features			
Operator	6.75 **	3.24	2.08
Hired staffs	8.52 ***	2.56	3.33
Farm size (ha)	0.15 **	0.08	1.99
Turnover_0.2-1 million	8.83 ***	2.77	3.19
Turnover_1-5 million	15.75 ***	2.87	5.48
Turnover_5 million and above	17.32 ***	3.15	5 .491
Intercept	-24.43	10.31	

Note: reference groups for educational level is "Senior high or below"; for farmer's type is "Self-employed farmer"; for annual turnover is NT$ 0.2 million or below. ***, **, * presents the significant level of 0.01, 0.05, and 0.1, respectively.

CONCLUSION

The study investigates the SA knowledge, attitude and adoption of farmers in Taiwan. Socio-demographic characteristics of the respondents and their relationships with the adoption of SA technologies are also determined. Survey data from 321 farmers participated in the SA training program were used. Findings reveal that there is significantly positive correlation among SA knowledge, perceived importance and adoption behavior. Out of eight SA technologies, the automatic environmental control system are the most well-known and important new technologies, while biological image detection and recognition technique are ranked as least known. In addition, the SA knowledge and importance also significantly influence the adoption of SA technologies. Lower adoption level of SA technologies might be attributed to inadequate information and missing knowledge, lack of awareness of the technologies and lack of practical value of application. The study therefore recommends intensification of adequate R&D of some SA technologies, such as IoT and big data analysis, to meet the farmers' need of current farming conditions and management. The main policy implication of this study can be inferred. These findings provide policy makers and agricultural educators with important insight, which can be used to better target interventions which build promote or facilitate the adoption of SA technologies. In addition, this study suggests that the agricultural R&D institutes need to concentrate on improving market access for well-known and high important SA technologies. And, providing systematic training courses related to applications of IoT and big data in agriculture may serve farmers better to engage in smart agricultural practices.

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