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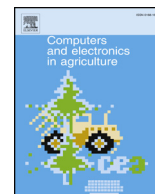
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A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems

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ABSTRACT

Precision agriculture has the potential to deliver improved and more sustainable food production. Despite the various Chinese policy initiatives to strengthen national food security, there is evidence that the adoption of precision agriculture technologies in China has been much lower when compared to other developed agricultural economies. This study therefore aims to explore factors that determine Chinese farmers' adoption of precision agriculture technologies in cropping systems and to provide recommendations on technology promotion in the future. The current status of precision agriculture adoption by smallholder farmers within crop farming systems in the North China Plain was explored. An integrated model of "Adapted Unified Theory of Acceptance and Usage of Technology (AUT²)" was developed to explain individual farmers' intention to adopt precision agriculture. 456 surveys were conducted via face to face interviews in the North China Plain and structural equation modelling analysis was used to estimate the proposed AUT² model. The results showed that perceived need for technology characteristics (PNTC), perceived benefits, perception of the efficacy of facilitating conditions and perceived risks of adoption have significant impacts on farmers' intention to adopt precision agriculture. The facilitating conditions (e.g. knowledge, resources and access to consultant services) were the best predictor improving Chinese farmers' willingness to adopt these technologies. Policy makers and service providers need to consider these factors in the promotion of technologies.

1. Introduction

The increase in the global population, coupled with increasingly

unstable commodity prices, has resulted in the need to improve the efficiency of food production to ensure equitable food security internationally. In recent decades, farmers have responded by increasing

Abbreviations: CB-SEM, Covariance-Based SEM; FC, Facilitating Conditions; GPS, Global Positioning Systems; GNSS, Global Navigation Satellite System; IPMA, Importance-Performance Map Analysis; ITA, Intention to Adopt; KE, Knowledge exchange; NC, Need Characteristics; PNTC, Perceived Need for Technology Characteristics; PLS-MGA, Partial Least Squares Multi Group Analysis; PLS-SEM, Partial Least Squares Structural Equation Model; PB, Perceived Benefits; PA, Precision Agriculture; RP, Risk Perception; SI, Social Influence; SRMR, Standardized Root Mean Residual; SEM, Structural Equation Model; TTF, Task Technology Fit; TC, Technology Characteristics; TAM, Technology Acceptance Model; UTAUT, Unified Theory of Acceptance and Usage of Technology; UAV, Unmanned Aerial Vehicle; AUT², Adapted Unified Theory of Acceptance and Usage of Technology; VIF, Variance Inflation Factor

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chemical inputs, such as pesticides and fertilizers, which has resulted in negative environmental and agronomic consequences (Lu et al., 2015). Farm production in China benefited from increased pesticide use after 2004, when the government began to eliminate agricultural taxes on farmers, and introduced three subsidies (i.e. a direct payment for grain production, a subsidy for improved seed varieties and a partial rebate for farm machinery purchases) (Chen, Fang, and Gao, 2010). In parallel, environmental challenges such as soil erosion and pollution, water scarcity, and the overuse of chemical inputs in China became a major social concern (Wilkes and Zhang, 2016). As a result, technological improvements in agriculture have been required to drive sustainable advances in labour productivity, farm incomes, food security and general economic growth (Maertens and Barrett, 2012), whilst reducing negative agricultural environmental impacts. One solution is to implement advanced agricultural technologies, such as precision agriculture technologies, so as to enable the more precise use of agricultural inputs (Kendall et al., 2017). Benefits resulting from application of PA have been identified, and include the following, inter alia; increasing efficiency, productivity and profitability in field operations; enhancing food security; and minimizing the unintended impacts of inputs on agricultural production systems and environment (Jochinke et al., 2007; Brown et al., 2016; Talebpour, Türker, and Yegül, 2015).

Precision agriculture (PA), a facet of site-specific crop management (SSCM) or precision farming (PF), represents a farming management concept based on observing, measuring and responding to intra-field variability in production (Lindblom et al., 2017; Li et al., 2019). Applications such as yield monitors (Ebel and Schimmelpfennig, 2011), unmanned aerial vehicles (Yang et al., 2017), polarimetric synthetic aperture radar (SAR) (Yang et al., 2019), Multi-GNSS precise point positioning (Guo et al., 2018) have been developed and applied in the agriculture production. Farmers' adoption of PA technologies have primarily occurred in more developed agricultural economies, such as the USA, Australia, Germany and the UK (Say et al., 2018), whilst the adoption rates are different globally, with lower rate of adoption in developing agricultural economies, such as China (Kendall et al., 2017).

In China, where the benefits of adoption are potentially high, there has been limited research into end-users' PA adoption in the farming community in particular those having smaller farms. Research projects on PA (e.g. "PAFiC", Precision Agriculture for Family Farms in China)¹ have been devoted to technology innovation, and pilot or trial projects using PA technologies have been launched (See Fig. 1). A case study in Heilongjiang Province (North-East China) reported that tractor auto-guidance is the most accepted with 25% of farmland equipped with certain forms of PA technologies (Verma, 2015). However, exploratory research conducted by Kendall et al., (2017) suggested that PA technologies are considered inaccessible, unsuitable and unnecessary for Chinese smaller farms. The slower pace of technology adoption in China in comparison with more developed countries may be partially attributable to a large number of producers being unfamiliar with PA technologies (Kendall et al., 2017; Clark et al., 2018). Notably, little research has been conducted to investigate the adoption and diffusion of these technologies amongst Chinese farmers.

The aims of the research presented here are 1) to propose a theoretical model and 2) to use the new model to explore the awareness of Chinese farmers in the North China Plain and their intentions toward adopting PA technologies. Key factors that facilitate and impede PA adoption in the Chinese context will be explored in the first instance, which is also applicable to other developing agricultural economies in the longer term.

¹ Precision Agriculture for Family Farms in China "PAFiC" is joint funded by the funded by the UK-China Research and Innovation Partnership Fund (Newton Programme).

2. Materials and methods

2.1. Theoretical background and hypotheses

Behavioural intention is an important predictor of behaviour that mediates the influence of internal perceived beliefs and external factors. It is a well-established theory in information system science and social psychology, although its predictive capacity may be limited by uncertainties associated with external factors (Venkatesh et al., 2008). To establish a comprehensive structural relationship between factors affecting PA adoption, the following eight hypotheses are proposed and tested in the conceptual model.

(1) Perceived need for technology characteristics (PNTC) of PA adoption

Technology utilization is governed by the match between technology features and the requirements of the task (Goodhue and Thompson, 1995). The perceived need for a technology depends on the alignment between the perceived capabilities of the technology and the task requirements. A good "task-technology fit" will promote users' adoption and a "poor task technology fit" will decrease the user's intention to adopt (Lin and Huang, 2008). Zhou, Lu, and Wang (2010) reported that task characteristics and technology characteristics have a significant impact on the task technology fit. Farmer's decision-making can be affected by their needs or demands. In this study, the perceived need for technology characteristics (PNTC) was adapted to the context of PA technologies adoption to measure the perceived fitness between farmers' need characteristics and technology characteristics. The perceived PNTC was predicted to be a significant precursor to an intention to adopt PA. In addition, it was assumed that PNTC will affect users' performance expectancy (Zhou, Lu, and Wang, 2010). In this study, the PNTC was defined as the capabilities of the technologies to match the needs of farmers, which was influenced by the need characteristics and technology characteristics and had an impact on perceived benefits and intention to adopt.

Hypothesis 1 (H1). Farmers' perceived need for the use of PA technologies will positively affect the farmers' PNTC.

Hypothesis 2 (H2). PA technology characteristics will positively affect the PNTC.

Hypothesis 3 (H3). PNTC will positively affect the intention to adopt PA.

Hypothesis 4 (H4). The PNTC will positively affect farmers' perceived benefits.

(2) Adapted Unified Theory of Acceptance and Use of Technology in PA adoption

Perceived benefits

The Unified Theory of Acceptance and Use of Technology (UTAUT) was first developed by Venkatesh et al., (2003) in the context of information technology (IT) acceptance research, which emphasised the main individual-level factors that affect behavioural intention and use behaviour from performance expectancy, effort expectancy, social influence, facilitating conditions and demographical factors. However, with agri-technology, which is a complex example, the users' perception of risks potentially plays a role in behavioural intention (Clark et al., 2018). To address this, this study adapted the UTAUT by adding perceived risks to the theory and proposed the Adapted Unified Theory of Acceptance and Use of Technology (AUT²) model to analyse farmer PA adoption. Perceived benefits have been considered to be the main driver that facilitated farmer adoption of new PA technologies (Pierpaoli et al., 2013). It is assumed that perceived benefits can positively influence farmers' intention to adopt PA.



Fig. 1. Precision agriculture (PA) equipment developed for farm management. For example, high precision positioning systems, laser land levelling, precision seeding/fertilizer/irrigation/harvesting and satellite images. Shown here is the GNSS tractor and UAV developed by the PAFiC project (<http://ceg-pafic.ncl.ac.uk/index.php/en/>).

Hypothesis 5 (H5). Perceived benefits associated with PA technologies will positively influence behavioural intention to adopt PA.

Facilitating conditions

Facilitating conditions may also play a significant role in removing barriers that prevent individuals from using a technology or a system (Venkatesh et al., 2003). Perceived access to PA resources and perceived ability to use these resources can promote a farmer's intention and willingness to adopt new technologies. Previous research has found a significant effect of facilitating conditions on technology adoption (Zhou, Lu, and Wang, 2010). In this study, access to financial support, necessary knowledge and resources and access to consulting services from professionals were used as proxies for facilitating conditions, as these have been identified as potential influencing factors in previous research (Kendall et al., 2017).

Hypothesis 6 (H6). Facilitating conditions have a positive impact on behavioural intention of farmers to adopt PA.

Social influence

Social influence may have a positive effect on a farmer's intention to adopt PA technologies. Social influence is defined as the extent to which an individual perceives it is important for others to expect a certain level of performance from an innovation or event (Venkatesh et al., 2003). It is similar to the subjective norm within the Theory of Reasoned Action inasmuch as it reflects the influence of external factors on attitudes and behavioural intention. In the current context, social influence is hypothesised to play an important role in the beginning of adoption as a factor, which potentially influences the individual's attitudes (Swinerd and Mcnaught, 2015). It is proposed that a farmer's behaviour is influenced by the way communities, peer groups, or other social influence encourage them to use PA technology.

Hypothesis 7 (H7). Social influence has a positive impact on a farmer's behavioural intention to adopt PA.

Perceived risks

Farmers' risk perceptions and associated attitudes can hamper the PA adoption rate (Tozer, 2009). For example, farmers could be reluctant to adopt the technology if the net impact potentially results in losses due to lower prices and revenues (Reichardt and Jürgens, 2009). Technical compatibility and financial cost might inhibit PA adoption by farmers. If farmers do not have financial resources and operational skills, they will not adopt PA technologies. Here, perceived risks were defined as having four aspects: financial risk, technical risk, production risk and management risk, and proposes the following hypothesis.

Hypothesis 8 (H8). Perceived risks associated with PA technologies

will negatively influence behavioural intention to adopt PA.

Demographic factors

PA adoption is dependent on the farm manager's knowledge and requires considerable investment in human capital (Daberkow and McBride, 2003). In this paper, moderating hypotheses were developed such that the decision makers' demographical characteristics have an impact on PA adoption. Hypotheses associated with demographic factors are listed below:

Moderating hypothesis 1: There is a significant effect of farming experience on the relationship among model constructs.

Moderating hypothesis 2: There is a significant effect of education on the relationship among model constructs.

Moderating hypothesis 3: There is a significant effect of farming dependence on the relationship among model constructs.

This research integrated PNTC and UTAUT models to generate a hybrid model to explain farmers' adoption of PA technologies, which aims to explore Chinese farmers' awareness and intentions toward adopting PA technologies in cropping systems and to figure out the key facilitators. This study has proposed a theoretical hybrid model to analyse the adoption of PA technologies, which could also be transferred to the analysis of general agricultural technologies or technologies in other domains.

2.2. Survey design

A survey was used to collect data in this study with questions formulated from the conceptual model (See Fig. 2) and demographical information. Each latent variable was measured by multiple items within the survey. Most of the items were adapted from the existing literature to preserve the content validity (Zhou, Lu, and Wang, 2010). New items were developed with reference to a recent UK-China funded study of PA in China (PAFiC project – <http://ceg-pafic.ncl.ac.uk/index.php/en/>). As part of the PAFiC project, a series of pilot interviews were conducted to gain a greater understanding of the factors influencing PA adoption (Kendall et al., 2017). The first draft of the questionnaire for this survey was developed from those pilot interviews and used adapted measurement scales that had been previously validated (Aubert, Schroeder, and Grimaudo, 2012).

A pilot survey was conducted with 28 farmers in Hebei and Shandong in March 2018 through telephone and online interviews. Based on the feedback from the pilot study, the questionnaire was refined to amend the translation bias to make the farmers more comfortable with the items, and a revised final questionnaire was developed. Five-point Likert scales were used in the survey, anchored by one to five (strongly disagree to strongly agree). The questionnaire was initially

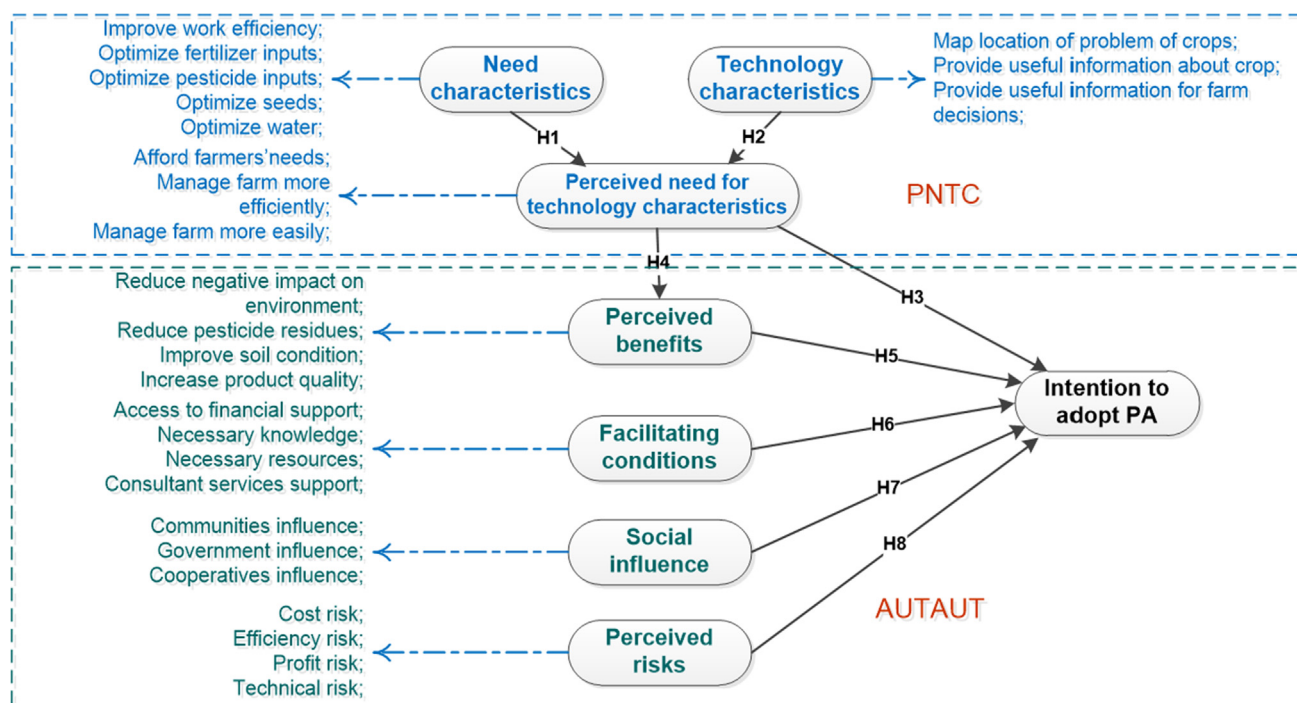


Fig. 2. Conceptual framework of this study. This is a theoretical model of intention for PA adoption that links a perceived need for technology characteristics (PNTC) with an adapted unified theory of acceptance and use of technology (AUT²) model. Multiple hypotheses are proposed to understand and model.

developed in English and then translated into Mandarin. Items with their respective latent variables are provided in Table 1. Identifying suitable PA technologies was performed using information retrieved from the existing literature (see (Clark et al., 2018)). The targeted technologies were precision soil sampling, yield mapping, GPS guidance and unmanned aerial vehicles (UAVs or drones). A farmer will be identified as an adopter of PA if he or she uses one of these PA technologies. An open-ended question was also added for those who did not continue to adopt and use PA to identify the main reasons why they stopped using PA (usually once a demonstration trial had finished) and to gain more general ideas on the consistency of PA adoption.

The research received ethical approval from Newcastle University before commencing data collection. Sample size design was based on the “ten-time rule” (i.e. the minimum sample size should be equal to the larger of the following: (1) ten times the largest number of formative indicators used to measure one construct or (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model) (Hair et al., 2016) which can be applied as a rough guideline for minimum sample size. Taking into consideration that demographic factors were also to be analysed in this study, a sample size of 450 was identified as appropriate, which met the ten times rule as well as those for multi-group modelling analysis.

2.3. Sampling and distribution

As the most important cropping system area in China, the North China Plain (NCP) (N32°~40°, E114°~121°) has been identified as a key region in securing national food supply (Lu and Fan, 2013). This study, therefore, chose three provinces (i.e. Hebei, Henan and Shandong, see Fig. 3) in this representative region for data collection to explore the PA adoption in the cropping systems in China. Data used for verifying the conceptual model were collected in April 2018 using random sampling combined with snowball sampling, with surveys completed face-to-face interviews with farmers. All farmer responses were anonymised. Random sampling was initially adopted to identify 1 city in each province and 1 county in each city, followed by 5 villages in each county. Following initial contact with local co-operative leaders,

farmers were recruited to take part in the survey. In total, responses were collected from 456 farmers (Henan 147, Shandong 124 and Hebei 185) and 449 used in this analysis. There were 7 responses excluded due to missing values. The sampling and distribution were chosen to reveal the perception of Chinese farmers’ attitudes toward environmental impact of agriculture, perception linked to PA associated factors and to verify the theoretical model built in the former part.

The sample showed a high diversity of farmers with regards to the main agricultural production area in China. The farm size ranged from 0.067 ha to 53.333 ha, with an average 1.306 ha. Still, 89.1% had ≤ 1 ha (where mu is the local measure of area and 1 ha equals 15 mu). Males comprised 45.2% of those interviewed, and age ranged from 27 to 85 years with an average of 59.5 years. 60.4% of the farmers were older than 56. This also verified the occurrence of urban migration of farmers moving from the agri-sector to other industries, leaving an aging population to farm the land. In terms of educational experience, 15.8% of farmers were educated < 6 years, 59.9% had reached 6 years but < 10 years and therefore had the ability to read and write, 21.2% had between 10 and 14 years of schooling and 3.1% had undertaken education for 15 years and above. Overall, 75.1% of the farmers had not received any professional education in agriculture and had acquired farming skills from the previous generation or short-term training courses.

2.4. Data analysis procedure

Structural equation modelling (SEM) is theoretically based on mathematical statistics and can describe and measure complex causality correlations. According to the rules for choosing a SEM method (Hair et al., 2017), Partial Least Squares SEM (PLS-SEM) was chosen to verify the hypotheses in this study for two main reasons: (1) the research objective is exploratory of theory based on total variance in the area of agricultural technology adoption and the objective of this analysis is prediction and (2) the research objective is to use latent variable scores in subsequent analyses. SmartPLS3.0 (<https://www.smartpls.com/>) was used for the analysis in this paper. Observed variables and their associated relationships with latent variables were

Table 1
Latent variables, indicator ID and corresponding questionnaire statements used within the survey.

LV	Indicator	Explanation	LV	Indicator	Explanation
Need Characteristics (NC)	NC1	I need to improve working efficiency on farming.	Facilitating Conditions (FC)	PB8	PA increases product quality.
	NC2	I need to optimize the level of fertilizer that I use.		FC1	I have access to the financial support I need to use PA.
	NC3	I need to optimize the level of pesticide that I use.		FC2	I have the necessary knowledge to use PA technologies.
	NC4	I need to optimize the amount of seeds that I use.		FC3	I have the necessary resources to use PA technologies.
	NC5	I need to optimize the amount of water that I use.		FC4	If I have any doubts about how to use the PA, there will be professionals to help me.
Technology Characteristics (TC)	TC1	PA allows me to map the location of problems with crops.	Perceived Risks (PR)	PR1	PA may increase the costs of farming.
	TC2	PA provides useful information about crop growing.		PR2	PA may not improve the efficiency of agricultural management.
	TC3	PA provides useful information for farm decisions.		PR3	PA may not improve the grower's revenue.
	TC4	PA allows me to manage my farm more efficiently.		PR4	PA may have technical risk.
Perceived need for technology characteristics (PNTC)	PNTC1	PA technologies can meet my needs.	Social Influence (SI)	SI1	Local communities encourage me to adopt PA on my farm.
	PNTC2	PA allows me to manage my farm more easily.		SI2	The Government encourages me to adopt PA on my farm.
	PNTC3	PA reduces water usage.		SI3	Cooperatives encourage me to adopt PA on my farm.
Perceived Benefits (PB)	PB1	PA reduces investments in seeds.	Intention to adopt (ITA)	SI4	PA helps me get a high positive profile amongst other farmers.
	PB2	PA reduces investments in fertilizers.		SI5	PA helps me to get certification for New type professional farmer
	PB3	PA reduces investments in pesticides.		ITA1	I would like to adopt PA in the future.
	PB4	PA reduces the negative impacts of agricultural activities on environment.		ITA2	I would like to be a service provider for PA.
	PB5	PA reduces pesticide residues.			
	PB6	PA improves soil condition.			
	PB7				

Note: LV refers to Latent Variable. All items are based on 5-point scale (1 indicates strongly disagree and 5 strongly agree). Abbreviations are shown in parenthesis.

described by the measurement models. Subsequently the structural model was tested to verify the hypotheses proposed in Section 2. Measurement models were tested in terms of validity and reliability from composite reliability, convergent validity and discriminant validity. The structural model was tested in four steps: multi-collinearity among latent variables, paths significance test, determinant coefficient (R^2) and predictive relevance (Q^2). Apart from analysing the path coefficients, the importance-performance map analysis (IPMA) was also conducted to obtain insights into the role of antecedent constructs and their relevance for managerial actions (Ringle and Sarstedt, 2016).

3. Results and discussion

3.1. Testing of the SEM model

A confirmatory factor analysis (CFA) was firstly conducted to examine the reliability and validities (both convergent validity and discriminant validity) by following a procedure proposed by Hair et al., (2016). Factor loading and cross loading were checked as the first step to the measurement model and PB1, PB2, PB3, PB4, SI4, SI5 and ITA4 were dropped. A PLS algorithm was applied to provide the results of the measurement estimations. The results indicated that most item loadings were > 0.7 and significant at the 1% ($p < 0.01$) level. Reliability analysis was achieved for each construct with composite reliability (CR) > 0.70 for all variables. Average Variance Extracted (AVE) represented the convergent validity of each construct and was achieved with all the constructs having an upper value greater than the threshold of 0.5. Discriminant validity was achieved by using cross-validation, Fornell-Lacker's criterion and Heterotrait-Monotrait Ratio (HTMT). The results of the multi-collinearity analysis showed that there was no multi-collinearity between latent variables in the structural model with a Variance Inflation Factor (VIF) < 5. A value < 0.10 or 0.08 (in a more conservative version) is considered a good fit. The Standardized Root Mean Residual (SRMR) for the model built in this paper was 0.058 (< 0.08), indicating that the model specification in this study is reasonable and further model examination is valid. All path coefficients were significant at the 0.05 level except for one. The results of path coefficient, path significance and effect size are shown in Fig. 4 and Table 2.

3.2. Prediction of PA adoption

Unlike the many information technologies (e.g. mobile banking) that are free for the end-user (Zhou, Lu, and Wang, 2010), costs needs to be taken into consideration when considering agricultural technologies adoption. Therefore, perceived risks were integrated into the UTAUT to determine farmers' perception in terms of cost risk, efficiency risk, profit risk and technical risk. Rather than using a TTF model, perceived need for technology characteristics (PNTC) was proposed to assess the fit between a farmer's (perceived) needs and PA technologies and determine their role in predicting PA adoption.

Within the adapted AUT² model, perceived benefits, facilitating conditions and perceived risks had significant effects on farmers' intention to adopt PA, although this was not the case for social influence. These results were consistent with those of previous research in Canada (Aubert, Schroeder, and Grimaudo, 2012). The results suggested that service providers need to conduct market segmentation and identify the need characteristic of different farmers' groups in order to differentiate their products and services to farmers with a good PNTC. As suggested by (Rogers, 1995), early adoption may lead to others following suite, the perceived benefit toward PA technologies and the intention to adopt PA among end-users should be promoted. The results also supported the correlation between PNTC and AUT². The PNTC was found to significantly affect the perceived benefits of, and intentions to, adopt PA. In addition, an important route identified for enhancing perceived benefits is to have a good PNTC for PA. For instance, if farmers are

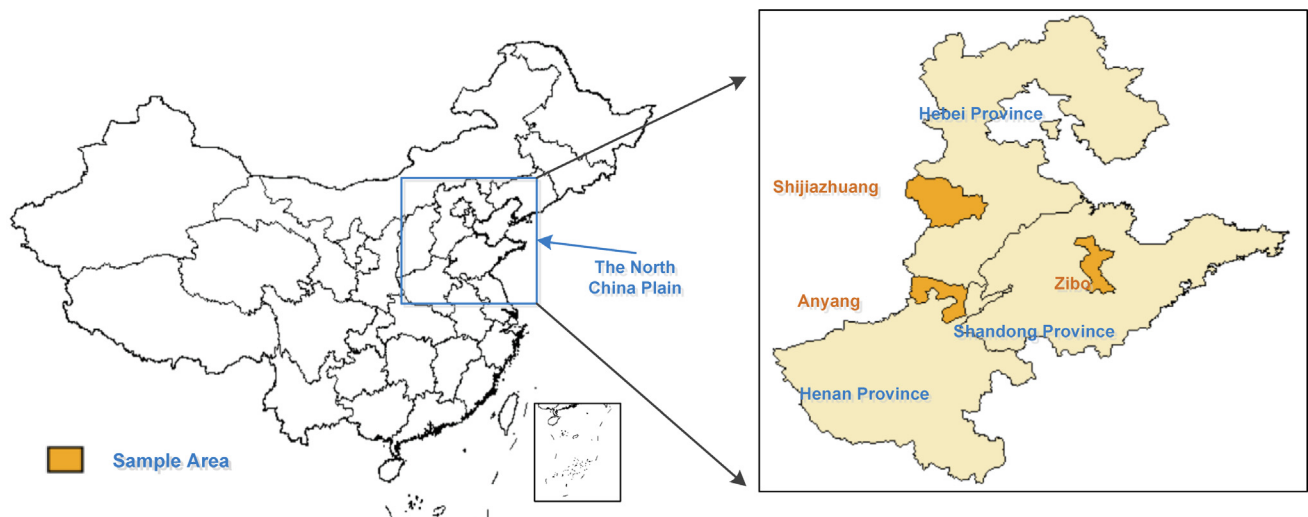


Fig. 3. Sampling area. Maps showing the location of the North China Plain region in China and the three provinces where sampling occurred (Henan 147, Shandong 124 and Hebei 185). Blue letters indicate province names, green words nearest town names and yellow dots indicate sampling areas. The main crops in this region were wheat and maize. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

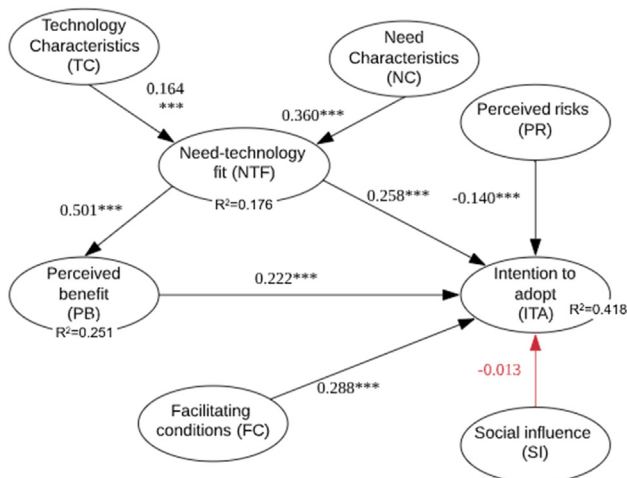


Fig. 4. Partial Least Squares Structural Equation Modelling (PLS-SEM) model estimation for intention to adopt of PA. ***P < 0.01, **P < 0.05, *P < 0.10; the red line indicated that the path from social influence to intention to adopt was not significant; R2 referred to the explanation of the amount of variance in endogenous latent variables (PNTC, PB and ITA). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

offered services that are do not fit with their demand for agricultural support, they will perceive these technologies to be less useful and to have lower perceived benefits. This reinforced the identified need for increased consultation with end-users regarding their needs, as well as the need to tailor communications about technology benefits to meet the needs of different end-user groups (Clark et al., 2018).

3.3. Current PA adoption assessment in China

The results showed that 53.2% of the farmers in the NCP had used PA technologies in the past but only 12.0% of the farmers continued to use PA technologies at the time of the survey. Farmers who took part in previous demonstration projects had a higher willingness to adopt PA in the future, and therefore were influenced by available resources. A farmer’s willingness to adopt PA in the near future was captured through four items: intention to adopt as a farmer, intention to adopt through cooperative structures, intention to adopt through (commercial) paid services, and willingness to adopt through being a service provider. 72.8% of the farmers who participated indicated that they will adopt PA in the next five years. The majority of the farmers in the NCP (> 70%) would like to use PA through a commercial service. Just under a third (32.1%) of the respondents wanted to be a service provider for PA and were looking for off-farm income diversity through providing a service to other farmers. Cooperatives were also captured in the survey as having a key role to play in PA adoption, with 62.4% of the respondents wanting to use PA with the help of cooperatives.

Table 2

Bootstrapping results of path estimation of structural model. ***P < 0.01, **P < 0.05, *P < 0.10; CI: Confidence interval; FC refers to facilitating conditions, NC refers to need characteristics, PB refers to perceived benefits, PR refers to perceived risks, SI refers to social influence, TC refers to technology characteristics, PNTC refers to perceived need for technology characteristics and ITA refers to intention to adopt.

Hypothesis	Path	Path coefficient	T value	S.D.	f ²	CI		Support or not
						Lower	Upper	
H1	NC → PNTC	0.164	3.697***	0.044	0.032	0.08	0.26	Supported
H2	TC → PNTC	0.360	8.031***	0.045	0.152	0.27	0.45	Supported
H3	PNTC → ITA	0.258	4.712***	0.055	0.079	0.14	0.35	Supported
H4	PNTC → PB	0.501	12.065***	0.041	0.334	0.42	0.58	Supported
H5	PB → ITA	0.222	4.526***	0.049	0.058	0.13	0.32	Supported
H6	FC → ITA	0.288	7.695***	0.037	0.122	0.21	0.35	Supported
H7	SI → ITA	-0.013	0.334	0.038	0.000	-0.02	0.12	Not Supported
H8	PR → ITA	-0.140	3.305***	0.042	0.027	-0.22	-0.06	Supported

Farmers did not adopt PA if they have never taken part in a demonstration project. There were slight differences in PA adoption at the provincial level. Farmers in Hebei and Shandong provinces had slightly higher adoption rates (12.0% and 13.7% respectively) in comparison to Henan province (10.6%), but there was no significant difference among the three regions (Pearson Chi-square = 0.619, $p > 0.05$). 1.78% of the surveyed farmers had purchased UAVs themselves. 32.52% of the farmers had taken part in demonstration projects held by the government focused on using UAVs to fine-tune fertilizer and pesticide applications and Global Navigation Satellite System (GNSS) guidance with sowing. The most frequent reasons given as to why PA adoption had not continued were that farmers cannot afford the equipment and cannot find a service provided by contractors. Some of the farmers argued that pesticide and fertilizer work completed using UVA was challenging in higher temperature conditions. Farmers in Hebei indicated that they had used the GNSS-enabled tractors for seeding work, i.e. by using the GNSS capabilities to measure farm size when calculating payments to the service providers.

3.4. Farmers' PNTC assessment

A framework was used to assess farmers' attitudes toward PA technologies from the perspective of need characteristics (NC), technology characteristics (TC) and perceived need for technology characteristics (PNTC). With regards to the proposed PNTC latent variables, the hypotheses proposed (H1-4) are supported. The results showed that in the PNTC model, constructs of need characteristics and technology characteristics were significantly positively related to a farmers' intention to adopt PA. The path coefficient from "need characteristics \rightarrow perceived need for technology characteristics (NC \rightarrow PNTC)" was significant with a low effect size ($f^2 = 0.032$), and the effect of path "technology characteristics \rightarrow perceived need for technology characteristics (TC \rightarrow PNTC)" is moderate ($f^2 = 0.152$). The hypothesis that PNTC had a positive impact on perceived benefits was supported ($\beta = 0.501$, $t = 12.065$, $p < 0.001$, $f^2 = 0.334$). The PNTC was observed to have a significant positive impact on intention to adopt PA ($\beta = 0.258$, $t = 4.712$, $p < 0.001$, $f^2 = 0.079$). The results showed that all the hypotheses of the PNTC were supported by the data.

Respondents gave a high score on the perceived need to improve the efficiency of on-farm operations. Fertilizer use and irrigation were identified as the two main inputs where efficiencies of use needed to improve. A strong desire to reduce the usage of pesticide was also identified. The farmers' perceived need to reduce the amount of seed was reported as less strong, mainly due to their belief that the technologies they use now for seeding are already precise, especially in relation to maize and wheat. Farmers believed that PA technologies can help them to gain useful information about crop management, assist with locating actions, and improve their farming decisions. Farmers also provided assessments about the technologies-need fit they perceived in terms of PA technologies. There was agreement that PA technologies were appropriate for them. The highest rating statements in the technology characteristics/need characteristics (TC/NC) section of the survey were that PA can help farmers to manage their farm more easily and more efficiently.

The main agronomic activities performed by Chinese farmers were analysed in this study. The adoption status in Section 3.2 reveals that there is a gap between trial and adoption. The results indicated that only a small percentage of farmers in the North China Plain were adopting PA approaches to moderate inputs associated with irrigation, fertilizer and pesticides. As variable rate irrigation technology is not as developed as fertiliser and pesticide, few farmers had adopted PA to optimise irrigation. The reason reported was that farmers need to install PA irrigation facilities by themselves rather than adopt these *via* a commercial service, i.e. there is a lack of support. Respondents gave higher priorities to improving fertilizer and irrigation efficiencies, followed by pesticide efficiencies. Although there were a certain

percentage of farmers that used diagnostic testing to inform pesticide and fertilizer inputs, farmers tended to be of the opinion that chemical pesticide and fertilizer inputs should not be reduced in order to maintain or improve yields. This is despite acknowledgement by farmers that agri-chemical overuse is common and problematic in China.

3.5. Perceived risks and perceived benefits

Initial investment cost, outside of pilot and demonstration support schemes, was the primary barrier to PA adoption identified by farmers. Farmers with small holdings held the view that it was cost prohibitive to buy the technologies as individuals, and they reported experiencing difficulties in finding an equivalent service provider. Accessible and affordable resources are the key to address cost issues. In addition, there is a need for service providers and policy makers to develop mechanisms to provide fiscal supports, such as subsidies or concessional credit. For farmers who have deeply rooted beliefs that current levels of fertilizer and pesticide must be maintained to ensure production efficiency, demonstrating productivity gains at lower levels of inputs is a potential route to altering their beliefs.

Research has suggested that a farmer's attitudes toward specific PA technologies, such as variable rate inputs, are primarily driven by the farmers' perceived benefits linked to using these technologies (Adrian, Norwood, and Mask, 2005). Farmers in the North China Plain perceived the benefits of PA technologies to be associated with the optimisation of water, seed, pesticide and especially fertilizer use. Reduced pesticide residue, improved soil condition and product quality were also identified to represent core benefits of PA. In contrast, the perceived risks of PA adoption were reported to be rather moderate. Perceived risks had a significantly negative impact on the intention to adopt ("perceived risks \rightarrow intention to adopt (PR \rightarrow ITA)", $\beta = -0.140$, $t = 3.305$, $p < 0.001$), but with a relatively low effect size ($f^2 = 0.027$). Farmers expressed higher risk perceptions to be linked to financial and technical issues. Removal of these (perceived and actual) barriers will be an important part of any successful PA adoption procedure. With learning and experience, and inducements to encourage more risk-averse farmers to adopt an innovation, the uncertainty associated with those risks will vanish (Daberkow and McBride, 2003). Policy makers, manufacturers and service providers should fully consider the negative effects of perceived risks, and work to improve technologies and management innovation to overcome these perceived risks toward PA. Making paid services a more affordable option, and increasing the number of service providers, can also facilitate adoption. Agricultural insurance could also be introduced into PA "packages" provided by service providers to mitigate farmers' perceived risks.

Some studies have examined the cost-benefit balance associated with adopting PA technologies. In the case of maize, for example, Schimmelpfennig (2016) reported that the profit improvement was positive, but only by a small amount. So far, there has been little evidence produced that crop products produced using PA technologies can have a higher market value. The main benefits of PA seem still to lie in the area of improved efficiency. The fact that financial risk was important, and costs were mentioned in the open-ended questions, implies that there is a need for more cost-benefit studies, to help allay some farmer concerns linked to cost and profitability, given that small profit improvements have been demonstrated elsewhere.

3.6. Facilitating conditions

PA adoption facilitating conditions perceived by farmers were linked to aspects of resources, knowledge, adequate financial support and access to professional consultants. The results showed that farmers' have perceived difficulty in finding resources to support PA, with only 20.3% having reported access to resources related to PA. Only 12.9% reported having the ability to gain access to knowledge related to PA adoption. Professional assistance was perceived as less of a barrier for

farmers to adopt PA, with 28.5% giving the response that they can find professionals to help when encountering issues associated with PA usage. 56.6% of the farmers reported difficulties in identifying financial support to adopt PA. Facilitating conditions were found to be at a moderate to low level regarding to PA adoption. Social influence was captured across three aspects (communities, government and cooperatives). Respondents gave a higher score regarding the perceived influence from the government, with an average score of 3.64. There were 60.6% of the respondents reporting agreement that they could be influenced by the government to adopt PA, compared with 45.4% for communities and 54.8% from the cooperatives.

In terms of facilitating conditions proposed in the AUT² model, significant positive effects were captured for the path “facilitating conditions → intention to adopt (FC → ITA)” ($\beta = 0.288$, $t = 7.695$, $p < 0.001$, $f^2 = 0.122$). This confirmed that a farmer’s intention towards adoption of specific agricultural technologies will increase when they can find resources and have the knowledge to realize it. When the technology fits farmers’ perceived needs, they will be more likely to adopt it. The results indicated that both farmers’ need characteristics (NC) and technology characteristic (TC) had a significant impact on PNTC, in line with previous studies on information technology (Zhou, Lu, and Wang, 2010). Organisations and manufacturers who produce PA technologies and services will need to consider the gap or fit between the technology’s characteristics and the farmers’ needs. In other words, even if a technology is perceived to be advanced by farmers, it will not be adopted if it does not fit a farmer’s need. For example, unmanned aerial vehicle applications are probably more appropriate for those farmers’ who grow conventional arable crops but will be inappropriate for those who farm greenhouse or covered crops. Greater consultation with end-users in relation to their needs is required to produce PA technologies that are relevant to Chinese farmers (Clark et al., 2018). Socialized agricultural services, especially for agricultural machinery, have proven to be an important pillar in building an intensive, specialized, organized and socialized agricultural management system in China (Zhong, 2015). However, these collective agricultural services have been mostly restricted to field operations and are unable to meet the emerging needs of modern agriculture (such as PA and smart agriculture). Therefore, new modes of collective agricultural services need to be explored, particularly in the context of delivering advanced agricultural technologies.

Facilitating conditions can predict a farmer’s intention to adopt PA. The results suggested that facilitating conditions had a significant impact on a farmer’s intention to adopt PA. Among the factors affecting a farmer’s intention to adopt PA, facilitating conditions had a relatively larger effect. Within the construct of facilitating conditions, resources and knowledge on how to use PA technologies were indicated as the core components that were vitally important to increase farmers’ intentions to adopt PA. Exposure to new information can act as an intervention, which will change individuals’ beliefs (Venkatesh, Thong, and Xu, 2012). In the context of agricultural technologies, the emergence of new facilitating conditions may stimulate adoption through influencing their beliefs and behavioural intention. Policy makers and service providers should need to consider farmer support services, such as training programmes and helplines, to enhance farmers’ knowledge and skills in relation to PA technologies. An individual’s beliefs are unlikely to change in the absence of information. The results suggested that the majority of farmers have difficulty in finding resources and support to implement PA technologies. Thus, policy makers and service providers should emphasise improving facilitating conditions for farmers. Interventions might include, for example, training on how to use computers or mobile digital devices (Daberkow and McBride, 2003).

3.7. Knowledge exchange

Contrary to the proposed hypothesis (H7), social influence was not

found to have a significant impact on intention to adopt PA. Hypothesis test results suggested that there was no significant result reported for the path “social influence → intention to adopt (SI → ITA)” ($\beta = -0.013$, $t = 0.334$, $f^2 = 0.000$), indicating that social influence does not have a significant influence on PA adoption. R^2 was interpreted as an explanation of the amount of variance explained by the endogenous latent variables. The results from this study showed that a moderate amount of variance ($R^2 = 0.42$) in a farmer’s intention to adopt PA technologies can be explained by factors identified in this study: technology characteristics, need characteristics, perceived need for technology characteristics (PNTC), perceived benefits, facilitating conditions and perceived risks. This contradicts the findings from UTAUT literature, in particular in relation to information system technologies (Zhou, Lu, and Wang, 2010), which implies that social influence has a significant impact on IS technologies adoption and diffusion.

Here, social information was associated with communities, government and cooperatives. Farmers indicated a higher preference for being socially influenced by the government. The analysis of the open-ended questions suggested that, even when social impact plays a role in increasing a farmer’s intention to adopt PA, adoption itself is still more likely to happen when there are no barriers to resources and knowledge to achieve the usage and when there are lower financial and technical perceived risks. Whereas most social groups can offer the former, only the government can reduce the financial and technical risks through subsidies, demonstration and trial programmes, emphasising the importance of government support in the future. Against this, local facilitating conditions might not be mature enough to support the diffusion of technologies, and it is difficult to demonstrate that social influence, such as encouragement from the government, communities and cooperatives, has a significant impact on a farmer’s intention to adopt PA. Further research is therefore required to establish if this is the case.

Demonstrations of agricultural practices and technologies can help adoption among agricultural producers (Rogers, 1995), but it appears that only when farmers can perceive the benefits of adoption, and win the perceived cost-benefit trade off, will they begin to use PA on their farms. Knowledge exchange can be used as a process to obtain knowledge about end-users’ requirements, enable identification of farmer priorities and assess the efficacy of proposed interventions to promote PA adoption. A key issue in accelerating adoption is the promotion of farmer understanding of the benefits of PA. Agricultural training and extension programmes need to be intensive enough to promote the benefits of diffusion of PA practices among farmers. Effective communication tools need to be explored and enhanced. Electronic media such as (specialised) TV, radio, internet and helplines can be developed to give more information on PA (Aldosari et al., 2017). In the context of PA in crop farming, the benefits of technologies could be quickly demonstrated on a commercial scale to potential end-users (Jochinke et al., 2007). Effective educational platforms, targeted demonstration activities, modifications in the curricula of educational institutions could also be used as communication tools to increase PA awareness and adoption (Yost et al., 2018). Mobile network coverage is increasing in China, as is access to cable TV, mobile phone or tablets. Developing simple but effective applications on mobile devices, coupled with training farmers in being able to use them, especially with the older farming generation, would be a logical step forward to address access and training issues.

3.8. Demographical effects

In this study, the role of demographics was also analysed, specifically the respondent’s farming experience, educational experience and farming dependence. PLS-multi-group-analysis (PLS-MGA) was conducted to capture the differences caused by the heterogeneity of these characteristics. The proportion of income from farming was used to represent a farmer’s dependence on farming. Each category was divided

into two groups: age (high (≥ 56 years) versus low (< 56 years)), farming experience (high (≥ 30 years) versus low (< 30 years)), education years (high (≥ 9 years) versus low (< 9 years)) and farming dependence (high dependence ($\geq 46\%$) versus low dependence ($< 46\%$)).

The results suggested that there is a slight difference in attitudes to PA adoption among groups according to farming experience and the extent to which farmers are dependent on agriculture for income (i.e. % of income generation). There was no significant difference in terms of educational experience. This differs to previous research which has indicated that the economic benefits of PA may outweigh the costs of PA if farmer is highly educated, in particular in relation to PA use (Paustian and Theuvsen, 2017). Full time farming has been shown to have a potentially positive impact on PA adoption in the USA (Daberkow and McBride, 2003), and evidence from Germany also indicates a higher PA adoption rate by the full-time farmers (34%) compared to the part-time farmers (11%) (Paustian and Theuvsen, 2017). However, in this study, farming dependence measured by the percentage of income from farming as a contribution to total income, played a significantly stronger role in perceived benefits, and subsequently on intention to adopt PA, by farmers with a higher dependence on farming. For farmers who viewed farming as their main income source, perceived risks had no significant impact on PA adoption. This implied that, for farmers with a low financial dependence on farming, interventions should be targeted at reducing their perceived risks.

The PLS-MGA for farming experience showed that there were two paths “technology characteristics \rightarrow perceived need for technology characteristics (TC \rightarrow PNTC)” and “facilitating conditions \rightarrow intention to adopt (FC \rightarrow ITA)” that differed significantly across the two groups. Technology characteristics had a stronger impact on perceived need for technology characteristics (PNTC) for farmers with less experience with PA. In terms of farmer’s education degree, heterogeneity was not captured and thus lead to the rejection regarding the categorical moderation role of farming experience in the model. There is a stronger impact of perceived benefits on intention to adopt for those who had a high dependence on farming. Perceived risks had a significantly negative impact on intention to adopt with farmers who depended less on farming. In contrast, for farmers with farming as their main income source, there was no significant impact of perceived risks on intention to adopt.

3.9. Priorities to improve intention to adopt PA

This study aimed to determine the key factors and priorities that influence, and are needed to improve, intention to adopt (ITA) and ultimately the development of PA in agricultural sectors. Importance-performance map analysis (IPMA) procedure proposed by Ringle and Sarstedt (2016) was conducted to explore the main factors that affect the endogenous latent variables through linear estimation separately: perceived need for technology characteristics (PNTC), perceived benefits and intention to adopt. The results of importance-performance map analysis (IPMA) are shown in Fig. 5.

In the endogenous construct of perceived need for technology characteristics (PNTC), a farmer’s need characteristics (NC) and technology characteristics (TC) were observed to have a significant positive impact on perceived need for technology characteristics (PNTC). The importance-performance map analysis (IPMA) results showed that a farmer’s perceptions toward technology characteristics played a more important role in improving the performance of perceived need for technology characteristics (PNTC). The importance-performance of need characteristics (NC) showed that it represents a secondary priority for improvement after the first priority-technology characteristics (TC). At the indicator level, providing useful information about farming decisions should be the first priority to improve the performance of the perceived need for technology characteristics (PNTC), followed by precision location and useful information on crop growth. This suggested that farmers are willing to obtain support information when

making a decision. This has an implication for manufacturers and research institutions inasmuch as it suggests they should devote effort into developing PA technology with more accessible support information for farmer decision-making.

From the PLS-SEM estimation above, perceived benefits had a significant positive impact on intention to adopt and therefore, an improvement in perceived benefits would potentially increase a farmer’s intention to adopt PA technologies. The results from the importance-performance map analysis (IPMA) at the latent variables level suggested that the perceived need for technology characteristics (PNTC) should be the first priority to improve the performance of perceived benefits. At the indicator level, the provision of easy and efficient technologies was suggested as the first priority to improve the performance of perceived benefits. Overall, facilitating conditions were identified as the most important priority to improve the performance of intention to adopt, followed by perceived need for technology characteristics (PNTC) and perceived benefits (PB). The results at the indicator level suggested that farmer knowledge and available resources to promote PA technologies need to be prioritised to improve PA adoption among farmers. Farmers’ perceived need for technology characteristics (PNTC) was identified as the second priority that can bring increased performance in intention to adopt.

4. Implications

From a practical perspective, institutions and service providers who have interests in promoting PA technologies need to improve the perceived need for PA technologies (potentially through demonstrating the agronomic and economic benefits), and the relevance of PA technologies to specific farmers’ requirements. Segmentation analysis could further be applied to understand different types of end-users (for example, working under different agronomic conditions) to optimize the technology characteristics and information design. Demonstration and training activities align with the practical requirements of end-users need to be held in local communities. In addition, agricultural machinery service or takeover service can be provided for farmers regarding the complex integrated technology. These activities need to be coupled with communication strategies which take account of farmers’ concerns and priorities, as well as technical issues related to PA implementation per se, which will require investigation *a priori*.

The research supported future adoption of PA technology measures in China. Promoting equity of access to innovative technologies by end-users is required and should be reflected in policy. Ensuring all farmers have equal access to innovative technologies is important as extensive adoption is to occur and deliver environmental and socio-economic benefits. The Chinese farming system faces challenges linked to the small size of farms, high levels of land fragmentation and rising labour costs (Zhang, Yang, and Thomas, 2017), as well as an increasing number of part time farmers, particularly in relation to cropping systems, where smallholder farmers represent a group yet to adopt PA. The research reported here has indicated that $> 70\%$ of participating farmers would like to exploit PA if it is to be provided through a commercial agronomic service. An example of trial was the consultancy service and subsidies schemes implemented by the Chinese government. For example, the delegated management service for agricultural production has been proposed to engage the ordinary farmers more directly in the process of agricultural modernization (MOARA, 2017a). The purchase of unmanned aerial vehicle (UAV) in 2017 was launched by Ministry of Agriculture and Rural Affairs (MOARA) with a subsidy discount of up to 30%, not exceeding 30,000 RMB for purchase, to motivate farmers’ or agronomic service providers’ investment (MOARA, 2017b). Future policy should also be designed to target equitable access to PA technologies across all farm scales and encourage the development of agricultural machinery services provided by agronomic cooperatives or companies.

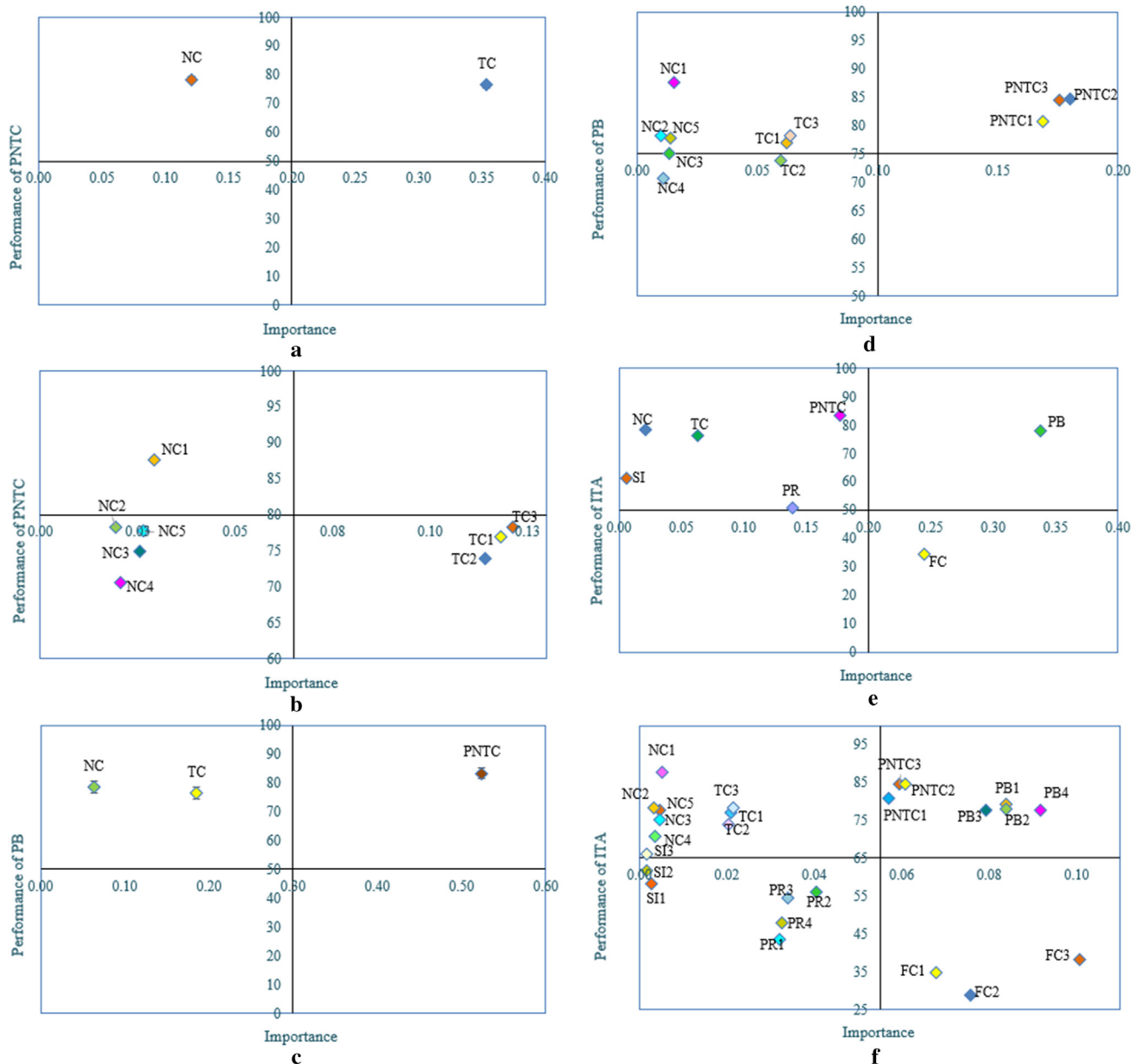


Fig. 5. Importance-performance map analysis (IPMA) results. 4a indicates IPMA matrix of perceived need for technology characteristics (PNTC) at latent variable level, 4b indicates IPMA matrix of PNTC at indicator level, 4c indicates IPMA matrix of PB at latent variable level, 4d indicates IPMA matrix of PB at indicator level, 4e indicates IPMA matrix of ITA at latent variable level and 4f indicates IPMA matrix of ITA at indicator level. **Abbreviation description:** FC: facilitating conditions, NC: need characteristics, PB: Perceived Benefits, PR: Perceived Risks, SI: social influence, TC: technology characteristics, PNTC: perceived need for technology characteristics, ITA: intention to adopt.

5. Conclusion

PA has great potential to contribute to agricultural production, as well as environment protection and food security (Gebbers and Adamchuk, 2010). However, the current adoption level of PA technologies in the cropping systems in NCP in China is low (with only 12.0% of farmers adopting PA), although there is little information available in the literature to explain why this is the case. Existing studies related to agricultural technology adoption have focused on understanding farmer’ behaviour change through understanding farmer perceptions, attitudes and the influence of socio-demographic factors in differentiating these. Little attention, however, has been paid to the fit between technology characteristics and farmers’ perceived needs for these characteristics. This study has addressed this knowledge gap by developing and testing a hybrid model which combines the perceived

need for the technology characteristics (PNTC) and “Adapted Unified Theory of Acceptance and Usage of Technology (AUT²)” models, to enable more accurate prediction about the facilitators of, and barriers to, Chinese farmers’ adoption of PA. This has enabled identification of key pathways to achieve PA adoption.

The results indicated that farmer perceptions of the benefits of PA, as well as the facilitating conditions for PA adoption, are important determinants of behavioural intention to adopt PA agricultural technologies. In addition, the link between farmers’ perceptions of their own needs and how well PA technology characteristics align with these also had a significant influence on farmers’ intention to adopt PA. Thus, the link between technology characteristics and farmers’ requirements need to be considered during the PA technology innovation process by policy makers and manufacturers. Consulting end-users and other interested stakeholders to ensure effective coproduction of PA

technologies is required at an early enough stage in the innovation process to ensure that PA technologies align with end-user needs. Facilitating conditions, such as knowledge, training and access to consultant services also need to be in place to encourage adoption. For example, with a strong vertical integration in machinery service supply as well as a fusion requirement of commercial and governmental services (Li et al., 2019), facilitating conditions in the Chinese agricultural economy need to be developed and be made accessible for farmers across all farm scales.

CRedit authorship contribution statement

Wenjing Li: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Beth Clark:** Conceptualization, Investigation, Writing - review & editing. **James A. Taylor:** Conceptualization, Investigation, Writing - review & editing. **Helen Kendall:** Conceptualization, Investigation, Writing - review & editing. **Glyn Jones:** Validation, Writing - review & editing. **Zhenhong Li:** Funding acquisition, Writing - review & editing. **Shan Jin:** Validation, Writing - review & editing. **Chunjiang Zhao:** Funding acquisition, Writing - review & editing. **Guijun Yang:** Funding acquisition, Writing - review & editing. **Chuanmin Shuai:** Writing - review & editing. **Xin Cheng:** Writing - review & editing. **Jing Chen:** Project administration, Writing - review & editing. **Hao Yang:** Project administration, Writing - review & editing. **Lynn J. Frewer:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.compag.2020.105305>.

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