**Evaluations of the roles of organizational support, organizational norms and organizational learning for adopting environmental-friendly technologies: A case of Kiwi fruit farmer’s cooperatives of Meixian, China**

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**Abstract**

Environmental friendly technologies have long been recognized as a ubiquitous phenomenon underlying the functions and performance of farms. Farmer’s co-operative organization might profoundly foster the EFT and availing competitive advantage to the farmer. Drawing on a natural-resource-based viewed of the farm (NRBV), this paper examined the impact of organizational support, organizational norms, and organizational learning on adopting Environmental Friendly Technologies (EFT) and proposed a model quantifying the influence of these practices on competitive capabilities (i.e., quality, cost, delivery, and flexibility). The model is empirically validated employing the partial least squares approach to structural equation modeling (PLS-SEM) based on survey data from a spectrum of 292 farmers of 38 Kiwifruit cooperative of Meixian County, China. The findings demonstrate that organizational support, organizational norms, and organizational learning positively influence environmentally friendly technologies (EFT). Moreover, the study found EFT positively impacts product cost, product quality, product delivery, and production flexibility. Interestingly, the relationship between the adoption of environmentally friendly technologies and the competitive capabilities of Kiwifruit farmers of Meixian is positively significant. The paper proposes several implications emphasizing the role of Organizations in the form of farmer’s cooperatives in encouraging farmers to engage in pro-environmental behavior and thereby shifting the attention of future research directions on the adoption of environmentally friendly technologies.

**Keywords:** adoption; impacts; bootstrapping; agricultural cooperatives; organization participation.

**Introduction**

Agricultural sectors are facing numerous challenges during the 21st century because it needs to provide additional food and fiber to support the ever-increasing population with very limited natural resources and far less rural labor which affect the overall growth of many developing countries mainly depending upon agriculture and demanding the adoption of more productive environmental friendly technology in responding to global warming, climate change and landfill problems (FAO, 2009; Grafton et al., 2015). In recent times, impressive technological advancements have been traced within the agriculture sector, which possessed a significant increase in productivity and efficiency, especially for supporting “the Green movement started in the early 1950s”. However, the adoption of environmentally friendly technology in agriculture differs significantly throughout various territories and agricultural practices (Zhang et al., 2020). The adoption rate and tendencies among the smallholder farmers of developing countries of Asia and African unions have been traced relative low (Adnan et al., 2019; Mondal & Basu, 2009; Omara et al., 2020; Rodriguez et al., 2009) and eventually limit their ability to enjoy the staggering advantages for enhanced agro-production, efficiency and opportunity to lead a better livelihood (Luo et al., 2016; Wreford et al., 2017). It is identical that well-structured agricultural transitions within the regions which tend to lower adoption rate fades away for tackling its economic, social, and ecological aspects and eventually indulge themselves into threatening condition for mitigating food security and poverty alleviation (Gibbs, 2000). Mostly, smallholder farmers in developing countries are not financially strong enough to bear the initial investments of accessing new technologies as well as the poor access of information, technical know-how, and weak negotiation abilities are also creating a burden for accessing new technologies, resulting in weak efficacy. These are including all associated costs for finding appropriate technologies to adopt, priority costs for initiating negotiations with suppliers and imposing contract assessment (Bingen et al., 2003; Zanello et al., 2014), which eventually hinders the agricultural efficiency (Courtois & Subervie, 2015; Seebens & Sauer, 2007).

For the elimination of the above-mentioned barriers, cooperatives organizations could act as a blessing for the smallholder farmers (Fischer & Qaim, 2012; Ortmann & King, 2007; Zhang et al., 2020). Cooperatives exist across most sectors of the economy and promote entrepreneurship, democratization, and the building of communities. Cooperatives are not charities (Harris et al., 1996; Prychitko & Vanek, 1996); rather, they are an organized group of self-help entrepreneurs who want to make a difference in their communities and region (Albæk & Schultz, 1998; Jepson, 2006). According to Birchall (2003), the history of cooperatives is full of evidence of their ability to increase their members’ incomes, decrease the risks they run, and enable them to become full participants in civic society. They have been especially impactful for securing smooth development in rural and regional areas. Around the world, cooperatives have played and continue to play an important role in helping people and small businesses to organize and foster better conditions and enable disparate groups to compete more favorably against larger industry players such as major corporations. In doing so, they have helped to promote greater equality within society, a role that is especially important at a time when digital transformations and modern forms of capitalism have tended to result in a concentration of power and greater disparity.

The co-operatives promote exchanges of knowledge between different farmers through organizational learning and raise the level of awareness of farmers. Activities undertaken by cooperatives today are playing an increasingly larger and important role in developing, and emerging countries, especially for a society like China that attaches great importance to ​​blood, kinship, and geography, members of the network can achieve adequate circulation and sharing of information through a mutual contact to exchange the ideas and concepts. In China, cooperatives in various forms have existed for almost a hundred years. Since the 1990s, China's agricultural agro-based cooperatives have flourished. This is mainly because local governments are now promoting the development of industrial organizations, which is an administrative requirement.

While organizing in cooperatives has been largely an ‘economic’ and community building movement, they have also served other roles. For example, historically, the ‘Gung Ho" ( 工合 "Gōnghé," meaning ‘work together’) industrial cooperatives movement in the 1930s started as a way to organize in order to increase production to aid in China’s ‘War of Resistance’ against occupying Japanese forces. Since the 1980’s a Chinese legal infrastructure and government support and encouragement have helped to encourage the growth of cooperatives and the economic development and community building they do. In modern China, there are hundreds of thousands of Chinese cooperatives, especially in the agricultural sector. According to the statistics of the Ministry of Agriculture and Rural Affairs, by the end of 2018, there were 417,000 agricultural-based industrialized organizations and 2.186 million farmers' cooperatives across the country, which led to nearly half of the country's farmers.

Interestingly, various researches have revealed the staggering impacts of farmer cooperatives for fostering modern technology adoption (Abebaw & Haile, 2013; Cafer & Rikoon, 2018; Kesiz Abnousi et al., 2020; Kolade & Harpham, 2014; Y. Wang et al., 2019). In an evaluation of Ugandan agricultural cooperatives, Mugisha et al. (2012) confirmed that Cooperative organizations possessed a positive and effective contribution for enhancing farmers' adoption tendencies towards ecofriendly technologies. The research of Kehinde et al. (2018) concluded that cooperative membership has a significant influence on the full adoption of improved technologies among Cocoa-Based Farming Systems of Southwestern Nigeria. Gong et al. (2019) discovered that cooperative participation consent Chinese (Anhui province) family-based farmers by providing better opportunities to gather in-depth information about innovative technologies and provides an advantageous place for exercising more productive and enhanced practices. By exploring the potentiality of information accessibility and capital endowment within cooperatives of Nigeria, Nwankwo et al. (2009) revealed that cooperatives are a strong medium to disseminate information, technical know-how, and case studies. The study also found that the information gathered from cooperatives is more trustable and reliable than any other sources. The empirical investigation of Ma & Abdulai (2019) confirmed that cooperative membership has an optimistic and substantial influence for exercising integrated pest management technologies and fostering efficiency resulting rise in net revenues and income. By evaluating a set of household data of Rural Nigeria, Wossen et al. (2017) confirmed that the cooperatives have greater encouragement power for adopting technology by facilitating credit access. Therefore, the participation of farmers in the co-operatives will have staggering impacts on the adoption behavior of farmers. However, farmer’s cooperatives are widely considered as a well-structured organization facilitating farmers mostly by exercising organizational support (Bernard & Spielman, 2009; Iliopoulos, 2013; Lafleur & Burtak, 2018; Verhofstadt & Maertens, 2014; G. Xu et al., 2020), organizational norms (Cropp & Ingalsbe, 1989; Hellin et al., 2009; Oliver, 1984; Wittenbaum et al., 2004), and organizational learning (Barton, 1989; Helmberger & Hoos, 1962; Hogeland, 2006; Idrus et al., 2018b; LeVay, 1983).

In Spite of having profound pieces of literature on the role of participating in cooperative on quantifying farmer’s adoption of modern, innovative, and eco-friendly technologies, but, empirical evidence of how and to what extent cooperatives facilitate the technology adoption extensity, more specifically how the organizational support, norms and learning interconnected with each other remains unclear. Moreover, there is a minimal piece of evidence that could be traced, which can highlight the impacts of these three aspects for fostering product cost, product quality, product delivery, and production flexibility and eventually availing competitive advantages. To address this knowledge gap, we examine the impact of cooperative membership on the technology adoption extensity using structured data collected from 292 Kiwifruit farmers of Meixian County, China, who participate in several cooperatives. To the best of our knowledge, the interconnection of the organization's supports, norms, and learning in the agricultural dimensions would be one of the novel studies and major innovations of the study.

The rest of the study is designed as follows. Section 2 is comprised of detailed background information, data descriptions, and methodology adopted of the study. Section 3 denoted the estimation procedures. Section four dedicated to comprising the results, and section 5 crafted for demonstrated the brief discussion. Section six has been designed for crafting the conclusion, policy recommendation, and limitation of the study.

**2. Methodology and Background of the data**

**2.1. Methodology**

The design of the study has been derived from a combined methodology of quantitative and qualitative approaches. The variables, indicators, and excerpt questionnaire items of the study have been comprised by an in-depth literature investigation, and the empirical parts of the study have been adherent by a survey data of 292 kiwifruit farmers. The model validation has been done by the structural equation modeling (SEM) tactics with the help of a survey data of 292 kiwifruit farmers. More specifically, we analyzed the results using Partial Least Square (PLS) of structural equation modeling (SEM), which is an estimation technique for the Structural Equations Model that combines the econometric perspective with a focus on the prediction and modeling of latent variables, resulting in greater flexibility in theoretical modeling. The PLS-SEM is considered multivariate tactics that broadly incorporate the existing knowledge with empirical settings and data-driven modeling (Hair et al., 2013). The PLS-SEM has been considered as superior to other SEM tactics like Covariant Base (CB-SEM), GSCA, and NEUSREL, due to its flexibility to work small data set, compatible with little available theory, paramount predictive accuracy, and versatility of handling various model (Wong, 2013). The tactics of PLS-SEM could be useful to envisage the latent dependent variables of the model by maximizing the explained Variance (R2). The main advantages of this approach are that it allows for exploring possible relationships between constructs, and it does not require samples with a normal distribution (May et al., 2019; J. Wang et al., 2017). As the agriculture sector is dynamic, and there is a hurdle to find normal sample data, PLS-SEM would be one of the best options as it does not need sample normalization. The PLS-SEM can be used in diversified fields as it assists the investigator to evaluates a complex relational modeling scenario with better accuracy and reliability, as suggested by Akter et al. (2017), Sarkar et al. (2020), and May et al. (2019). Several studies with similar dimensions also utilized the PLS-SEM to measure the effects of some certain activities, such as; Mutyasira et al. (2018), Ferraz et al. (2018), May et al. (2019), Guzmán et al. (2020), and Idrus et al. (2018a).

The study adopted a three-step methodology to maintain profiling validity of model and content, as suggested by Dang et al. (2014), Wong (2013), and May et al.(2019). First, the variables and indicators have been comprised by an extensive literature review; in the second stage, a pilot test has been done to find any conceptual inconsistency or bias content. After adjusting the questionnaire (as per the observations gathered from the pilot test) in the third stage, the study purified all the latent variables as per the factor loading and coefficient alphas. Upon achieving the content validity, the reliability of the measurement has been identified by securing the indicator’s reliability, internal consistency, convergent validity, and discriminant validity.

**2.2. Operationalization of latent variables**

The study has comprised of five latent variables, which are primly multidimensional, and it cannot compute within a single construct/indicator. Therefore the study utilized several indicators comprised from the past literature for measuring each of the latent variables, as shown in figure 1. The level in which members feel that the organization values their efforts, concerns for their health as well as addresses social, physiological, and social needs are considered as the ground of organizational Support (Rhoades & Eisenberger, 2002). The first three exogenous variables (a prime component of organizations) of the model (Organizational support, Organizational Learning, and Organizational norms) have been comprised as the interactions of the organizations, and the three-component could be important elements for the kiwifruit industries technology adoption (G. Xu et al., 2020). Organizational supports (OS) could be derived from prospects of emotional support and instrumental support (Colbert et al., 2015; Mathieu et al., 2019). The well-known study by Rhoades & Eisenberger (2002) and Colbert et al. (2015) has been utilized to formulate the indicators OS\_8 and OS\_9. The indicators OS\_1, OS\_5, and OS\_6, has been taken from the study of G. Xu et al. (2020), and the indicator OS\_10 and OS\_12 have chosen from Frambach & Schillewaert (2002). While the indicator number OS\_11 is the authors’ contribution. Organizational learning (OL) is defined as the process in which farmers continue to acquire knowledge, improve their behavior, and optimize their organizational participation by organizing training, interactions, and learning from members so that the organization can maintain its survival, development, and growth (G. Xu et al., 2020). The indicators OL\_2, OL\_3, and OL\_5, have been taken from the study of G. Xu et al. (2020). OL\_6, OL\_9, and OL\_10 have been comprised from the study of Jiménez-Jiménez & Sanz-Valle (2011) and Deji (2005), and the indicators OL\_7 and OL\_7 is the contributions of the authors. The organizational norm (ON) is defined based on mandatory external pressures and the organizational environment, the process in which the individual gradually agrees with the norm in the process of compliance and then achieves the internalization of the norm. “t” mainly includes normative pressure and organizational guidance. Indicators ON\_1, ON\_2, ON\_3, ON\_6, and ON\_7 have been taken from G. Xu et al. (2020), and indicators ON\_4 and ON\_10 are the author's contributions.

The three indicators of the latent variables four have been taken from the relevant study regarding adoption, e.g., Cakirli Akyüz & Theuvsen (2020), Mutyasira et al. (2018). Finally, the indicators regarding competitiveness have been taken from the study of Kumar Mittal & Singh Sangwan (2014) and Cakirli Akyüz & Theuvsen (2020). Based on the above discussion and extensive literature investigation, the study crafted four hypotheses:

**H1:** Organizational Learning is positively correlated with farmers of co-operative to adopt EFT.

**H2:** Organizational Support is positively correlated with farmers of co-operative to adopt EFT.

**H3:** Organizational norms are positively correlated with farmers of co-operative to adopt EFT.

**H4:** The adoption of EFT positively influences to foster the competitiveness of the farm.

**Figure 1: Conceptual model**

**2.3. Area of Data collection**

The empirical data of the study has been extracted from the Kiwifruit framers of Meixian Country, Shaanxi Province, China. The province is well recognized as the birthplace of China’s modern agricultural civilization, one of the most innovative agricultural provinces in China. In terms of the Kiwifruit industries of Shaanxi, it accounts for about 40% of the country, ranking first in the country, and possessed unique advantages and foundation for the kiwifruit industry. Meixian is Shaanxi’s beating heart for the development and expansion of modern kiwifruit cultivations. There is a popular saying that China's Kiwifruit will follow the example of Shaanxi, and Shaanxi's kiwifruit industry shall follow the example of Mei County, where the major peak of the Qinling Mountains is located. Mei County, located in the core area of the kiwifruit industry, is already the main and best area of Kiwifruit growing in Shaanxi. As early as 1200 years ago in the Tang dynasty, there was a poet called Cén Shēn who had a poem describing kiwifruit trees. In recent years, Mei county had a fast development in the kiwifruit industry by making use of the unique advantages like appropriate locations, plenty of various resources, robust technical support, and industrial circumstances. There are total kiwifruit cultivation areas reaching 21,000 ha, accounting for one-third of the totKiwifruit growing area in Shaanxi province, one-fifth of the total Kiwifruit growing area in China, and one-tenth of the world total. Total yield per year reached 460,000 t and output value reached RMB 3000 million yuan, which makes Mei County an iconic county of the kiwifruit industry in Shaanxi or even in China (Song Jingli, 2017). Four most important advantages make Meixian County stand out in kiwifruit industry: i) ecological environment, due to locations in the north slope of Qinling Mountains and Qinling-Ba mountainous area where there is very good natural conditions for kiwifruit trees; ii) rich germplasm resources, due to Qinling mountains to be regarded as the gene bank containing plenty wild kiwifruit resources, out of which there have been 18 elite varieties selected and bred ripening in periods from early to late and with sarcocarp in green, yellow or red color; iii) science and technology, due to dependence on the support from Yangling State Agricultural High-tech Demonstration Zone and Northwest A&F University, which makes whole supply chain of kiwifruit industry covering breeding, cultivation, storage, packaging, transportation and marketing well integrated by technological and standards system; iv) marketing, due to famous brand of Kiwifruit developed by leading companies and marketing teams through integrating the organic fruits strategy and protected designation of origin (PDO), which makes kiwifruit industry another highly competitive industry following apple in Shaanxi (Zhande Liu, 2019). Meixian has also been recognized as “National Kiwifruit Standardized Production Demonstration Zone,” “Top Ten County of Chinese Fruit and Vegetable Standardization Construction,” and “China Kiwifruit Pollution-free Technology Demonstration County” (G. Xu et al., 2020).

**2.4. Prospects of the study**

Agricultural and rural development in Shaanxi resembles the broader situation of Chinese agriculture, which is dominated by a smallholder farming structure, a large share of the rural population, and high rural-to-urban migration rates. Due to the small farm size, agricultural income can rarely support the livelihood of rural families. Most of the young generations of farmers opt for migration to the cities, either seasonally or permanently, in search of better income opportunities in industrial or service sectors, while elderly farmers and women remain in the villages for undertaking farm works (G. Xu et al., 2020; Zhang et al., 2020). The smallholder structure and scarcity of rural labor provide ample opportunities for the development of farm cooperatives that support the pooling of production inputs (e.g., land and capital) and facilitate the adoption of labor-saving technologies (e.g., harvesting machinery) (Y. Xu et al., 2017). In other words, cooperatives may help to facilitate the transition from labor-intensive smallholder farming to a capital-intensive farming system, which is a key for the agricultural modernization of Chinese agriculture. Especially after the national farmer cooperative law was issued in 2007, the number of farmer cooperatives in Meixian has increased at an unprecedented pace. Meixain County is a prime Kiwifruit demonstration Zone of Shaanxi province and a key national cooperatives model desaturation zone as well. The cooperative of Meixian County has won some profound awards. For example, Qifeng Selenium Rich Kiwi Fruit Professional Cooperative was awarded as top 100 Provincial Strong Demonstration Cooperatives by Provincial Cooperative in 2010 and National Cooperative Model by Ministry of Agriculture of China in 2012. It is therefore timely to investigate the relationship between organizational learning, support and norms in terms of facilitating the farmers' adoption of EFT and data from Meixian would be representative.

**2.5. Data Collection**

We utilized multistage cross-sectional tactics for choosing the appropriate farmers for our study. First of all, we randomly selected 12 towns of Meixian, which has the most number of farmer’s co-operatives and prime Kiwifruit cultivation area. After that, we randomly selected six towns that have the most number of Kiwifruit cooperatives. We further randomly selected 5 to 8 villages each within those six towns, which comprised a total of 38 co-operatives mainly working on Kiwifruit. We have conducted a pilot test with randomly selected 50 farmers. Finally, we selected 8 to 12 members from each cooperative, and a face to face interview has been conducted with a randomly selected 430 members of those cooperatives. As a multivariate tactic, PLS-SEM does not demand strict sample size and data normalization (Afthanorhan, 2014); determining the appropriate sample size for producing an effective PLS-SEM model is a tricky question (Wong, 2013). Hence, Hoyle (1995) and Hair et al. (2013) suggested that at least 100 observations could be the starting point for securing the path estimation. Interestingly, Marcoulides & Saunders (2006) addressed that the minimum sample size could be determined by the maximum number of arrows pointing at a latent variable. They suggested that if the maximum number of arrows counts as two, the minimum sample size should be 52. If the arrow number is five, then the sample should be 70, and if the arrow count is ten, then the minimum number of the sample should be comprised of at least 91 observations. With the help of a structured questionnaire, we gathered 292 responses with full information (those do not contain any missing information). Therefore, the final data set of 292 farmers has secured all the above-discussed parameters of minimum sample size. Moreover, Table 2 shows the Kurtosis and Skewness values are between ±1, which confirms the data normality is within the acceptable limit. The design of the questionnaire has been set as a two-part, first part demographic profile of the respondent has been gathered and the second part of the questionnaire has been comprised with 5 points Likert scale where one denotes the Strongly Disagree, 2 Disagree, three neutral, 4 Agree to some Extent, and five means strongly agree (excerpt questionnaire used in the study has been demonstrated in Supporting file Table S1). In particular, we collected data on the adoption of environmental friend technologies (production and post-harvest).

**3. Estimation procedure**

There are two types of measurement scale in structural equation modeling; it can be formative or reflective. If the indicators are highly correlated and interchangeable, they are reflective, and their reliability and validity should be thoroughly examined (Hair et al., 2013; Sarkar et al., 2020). In the course of the study, we have utilized the reflective measurement scale. The estimation of the process of the study has been comprised of two stages. Partial least squares structural equation modeling (PLS-SEM) has been comprised in the first stage to examine what extend the three construct (organizational support, organizational values, and organizational norms) derived the adoption of EFT. In the context of the study, the adoptions of EFT are latent variables which directly unobservable. As an alternative, a set of excerpt questionnaires has been used as indicators for comprising the fundamental latent variables. The SEM model encompasses an outer model that identifies the interrelationship among the latent factors and underlined indicators, and an inner model comprised the interrelationships among the dependent factors and independent latent factors highlighting the path coefficients of those factors (Wong, 2013). The second stage comprised of a model that quantifies what extend the adoption of EFT lead the competitiveness in the form of cost reduction, maintaining high-quality production, efficient delivery, and production flexibility. For the prospects with the study, we have added independent variables in the SEM model explained earlier, which is synthesized with the theory of competitive advantages and akin researches (Asfaw et al., 2012; Barone & DeCarlo, 2003; Gandhi, 1997; Requier-Desjardins et al., 2003). Figure 1 denotes the combined model used in the study.

**4. Results**

This section stated the results attained after analyzing the questionnaire. First of all, we described the demographic information of the sample, following by a procedure to estimate the common method bias-ness. After that, the results of the PLS-SEM have been comprised of four-phase: reliability and validity test, measurement model, structural model, and checking structural path significance in bootstrapping.

**4.1. Demographic Profile**

The kiwifruit farmers studied in the research has found on average 37 years old (SD=5.8), 77% of them are male, most of them has at least primary education (37%), 22% of the farmers has high school degree, only 13% of them are undergraduate or above and rest of 22% are illiterate. Moreover, we found most of the farmers used production/pre-harvest environmentally friendly technology (67%). Nearly 88% of the EFT has been introduced to them by co-operatives, and the rests of the farmers are aware of the EFT before joined the co-operatives. Descriptive statistics of key variables are stated in table 1.

**Table 1 Descriptive statistics of key variables.**

**4.2. Common Method Bias Test**

Since all of the elements in the survey were estimated with a specific form of the respondent (farmers from the kiwifruit co-operatives) and a five-point Likert scale, a typical methodological bias may therefore exist throughout this analysis. Thereby, the effect of the common method bias has been sincerely evaluated. While there are a limited number of forecasts are present for determining the impact of common method bias (Tehseen et al., 2017), we adopted two steps approach of defining the issues of common bias, i.e., Harman’s single-factor test and correlation matrix procedure (See supporting file 2). Overall interpretation of table S3 shows that the dataset does not contain any single factor bias issues, and the values of first factors also did not lead with the most Variance. While this investigation did not find the problem of common method bias, the dataset is therefore valid for further evaluation.

**Table 2 Validity of constructs (Reflective Outer Models)**

**4.3. Results from the PLS-SEM approach**

For assessing the PLS-SEM approaches, the study utilized the procedure of; (i) Explanation of target endogenous variable variance, (ii) Inner model path coefficient sizes and significance, (iii) Outer model loadings and significance, (iv) Indicator reliability, (iv) Internal consistency reliability, (v) Convergent validity, (vi) Discriminant validity, (vii) bias test and (viii) Checking Structural Path Significance in Bootstrapping as suggested by Wong (2013), May et al. (2019) and Munim & Noor (2020).

**4.3.1. Measurement model**

The assessment of the results of the study starts with the evaluation of the measurement model. The measurement model produced by the data revealed in figure 2 stated the interrelationship on how all the latent variable is quantified by the observed variables. According to Wong (2013) and Sarkar et al. (2020), for providing a smooth transition and quantify a reliable and valid PLS-SEM model indicator reliability, internal consistency reliability, convergent validity, and discriminant validity could be measured Average Variance extracted (AVE). Table 2 summarizes the outcome that showed the reliability and validity of the model. Table 2 denotes the standardized factor loadings of the CFA framework, all of which statistically viable (p-value<0.001), representing that the variables replicate their fundamental latent paradigm. This endorses the convergent validity of the framework, as suggested by Anderson & Gerbing (1988). Table 2 also represents the Cronbach’s alpha, composite reliability (CR), and average Variance extracted (AVE) of all the indicators. The CR has been crafted by utilizing the following equation suggested by Hair et al. (1998):

$CR=\frac{(\sum\_{i=1}^{n}fl\_{1})^{2}}{(\sum\_{i=1}^{n}fl\_{1})^{2}+ (\sum\_{i=1}^{n}ME\_{1})}$ 1

Here, FL1 is the standardized factor loadings of measurement item $i$,$ n$ is the number of items in a factor, and ME1 is the measurement error of the item $i$. ME1 is crafted from: $\sum\_{}^{}1-fl\_{1}^{2}$.

Table 2 indicated all the indicators passed the threshold value of 0.07 (Hair et al., 2013). Therefore, the study possessed a strong validity of the conceptual framework. The next assessment is to confirm the Divergent or discriminant validity (DV), and to confirm the DV, squared-correlations of all latent variables should be measured in a matrix and compare with their average Variance extracted (Fornell & Larcker, 1981; Munim & Noor, 2020). Average Variance Extracted (AVE) has been crafted for satisfying the convergent validity and DV by using the following equation crafted by Hair (1995):

AVE= $\frac{\sum\_{}^{}\sum\_{i=1}^{n}fl\_{1}^{2}}{n}$ 2

Here, FLi is the standardized factor loadings of measurement item$ i$,$n$ is the number of items in a factor. As table 2 indicated that AVE for all the indicators is well secured with the accepted values of 0.5 (Bagozzi & Yi, 1988). The study comprised Fornell-Larcker Criterion for providing DV as portrayed in Table 3. The table showed that squire root values are greater than the correlated values of all the associated indicators, which secured the DV as subsisted by Hair (1995). Additionally, Table 2 showed that CFI (Comparative Fit Index) and TLI (Tucker-Lewis Index) holds higher values than the accepted value 0.90, the RMSEA (Root Mean Square Error Approximation) and SRMR (Standardized Root Mean Square Residual) denoted the lower values than the threshold of 0.08 (Hair et al., 2013). Therefore the measurement model is confirmed as a substantially good fit.

**Table 3 Fornell-Larcker Criterion Analysis for Checking Discriminant Validity**

**4.3.2. Structural Model representation**

After confirming the reliability and validity of the measurement model, the next step is to fit the measurement model ion to the structural model. The interconnection between the latent variables and their associated indicator has been developed within the structural model Wong. (2013a) suggested that the common method bias test followed by bootstrapping (PLS based multivariate bootstrapping) should be used for providing a clear and viable structural model. Bootstrapping is a nonparametric tactic that consents to observe the statistical significance of various PLS-SEM outputs, for example, path coefficients, Cronbach’s alpha, and R² values. Bootstrapping procedures firstly indulge in the measurement of the mean and Variance of all latent variables, and after that, actual mean and Variance has been compared with t-statistics. The above mechanisms, therefore, assist in identifying the T-value evaluation and ensure that the structural pathway approximation remains accurate (Streukens & Leroi-Werelds, 2016). A significant set of different observations (for example, 5000) were collected first from overall substitution samples to generate bootstrap sampling error and then provide the systemic direction estimated T-values. In PLS-SEM, bootstrapping has to be used for providing a consistent construct and outcomes (see Table 4 and Table 5). As demonstrated earlier (Table S3 supporting file 2), the study does not contain any issues of common method bias. Therefore the study utilized two-tailed t-tests at a 5% significance level (see table 5). The factor loading of the entire set of variables (outer model) contains values more than 0.7 (see fig. 2). Therefore it indicates the factor loadings hold the minimum established value as suggested by Hair et al. (2012). We have used “SmartPLS-3” software to measure the factor loading of all the variables and “t-test” as portrayed in table 4 (inner model) and table 5 (outer model). Tables 4 and 5 indicated that the value is well above the accepted value of 1.96, which confirms there is significant interaction among all of the latent variables (Mutyasira et al., 2018) and the model holds statistically viable values.

**Figure 2 PLS-SEM results of the proposed model.**

Table 6 signifies the prime outcomes of the study, and it indicates the model represents considerable measurement loading for the entire set of associated indicators. The structured framework established a statistically viable and significant interaction that has also been found among all the indicators. Moreover, all the associated theories and hypotheses are legitimately reliable as tested by T-measurement estimation.

**Table 4 Bootstrap results of the model (inner model)**

By considering the above viewpoint, the study concludes the final results as:

**H1:** Organizational Learning is positively correlated with farmers of co-operative to adopt EFT **(accepted).**

**H2:** Organizational Support is positively correlated with farmers of co-operative to adopt EFT **(accepted).**

**H3:** Organizational norms are positively correlated with farmers of co-operative to adopt EFT **(accepted).**

**H4:** The adoption of EFT positively influences to foster the competitiveness of the farm **(accepted).**

**Table 5 Bootstrap results of the model (outer model)**

**5. Discussion and implication of the study**

The effective adoption of EFT among the farmers can result in a step forward to green and sustainable farming planning, which considered as a prime dilemma of the modern world, especially for the growing economy as most of the framers possessed low awareness, skills, and technical know-how about EFT (Isik, 2004). For fostering the influence of farmer’s organizations or co-operatives might have a substantial impact to facilitate the smooth adoption transition (Abebaw & Haile, 2013). As a result government of China has established several policy recommendations to uphold the importance of co-operative organization (Loubere & Zhang, 2015). But the understanding of the adoption of farmers mostly depends on distinctive factors and likely complicated too. Especially, the growing economy like China, where personal relationship, support, and mutual understanding play a crucial role in profiling farmer’s behavior to a great extent and thus it is expected the interaction of the farmers’ co-operative in the form of organizational support, organizational norms, and organizational learning might be profound (G. Xu et al., 2020). Thus based on extensive literature investigation, the study comprised 23 indicators that can foster three key variables (Organizational supports, learning, and norms) and build a structural model that represents the interrelationship between the adoption of EFT. Moreover, the studies extended the model by measuring the effects of adoption in the forms of a competitive advantage, which is the key innovation of the study. The conceptual model then measured, structured, and statistically verified with the help of 292 farmers from 38 Kiwifruit cooperative of Meixian County, China.

**Table 6 Parameters of the structural model**

The study comprised substantial effects of organizational supports for maintaining smooth transition for adopting EFT, which is parallel with the results of Aubert et al. (2012). Parallel with the outcomes of Lee (2005), the impacts of organizational learning within the Meixian kiwifruit farmers are also found relatively high. Though the interaction of organization norms for adopting EFT is significant, however organization supports and learning possessed better influence than the organizational norms, which is quite different from the study of Lynne et al. (1995) and Higgins et al.(2017). Overall the study comprised a staggering relationship among the key variables of organizational supports, organizational learning, and organizational norms. Interestingly, parallel with the existing research on farmer’s adoption of environmentally friendly technology (Mahfudz et al., 2019; Ogunlana, 2004; Tal, 2018), the study also found a substantial impact of EFT for availing competitive advantage.

While Yigezu et al. (2018) found initial investment somehow hinders the adoption and scaling up sustainable, eco-friendly technology among Syrian wheat and barley farmers. The studied farmers also provide greater emphasis on the initial investment as the factors loading of the variables regarding initial investment (OS\_11) found so relatively high. Provision to credit and off-farm earnings can significantly reduce restrictions on flexibility and thereby increase access to appropriate technological, operational, and resource supplies (Doss, 2006; Migliorelli & Dessertine, 2018); the current study has also traced a sufficient influence of credit/loan facilities assessed by the organizations (OS\_5). As most of the environmentally friendly technologies in China are relatively new, that could be possible that the study found, training facilities have substantial impacts on adoption (Rola‐Rubzen et al., 2020; Suvedi et al., 2017). Parallel with the results of Doss (2001), and the study comprised a substantial impact of farmer's experience (OL\_6 and OL\_7) on EFT adoption. Mwalupaso et al. (2019) found strong associations and networks of the adoption of EFT and the concepts of cleaner production, which is quite similar to our findings. Organizational encouragement for maintain cleaner production tactics and fostering social responsibility (ON\_1) found positive within the Meixian kiwifruit farmers. The study revealed that as the co-operative organization handles the short-term risk (as EFT might not produce an instant outcome), the farmers most likely are on the happier side to adopt EFT (ON\_10), which reflects a similar finding of Liu (2013). As information-sharing facilities provided by co-operative organizations can foster the transitional effects among the farmers (Zheng et al., 2019), the study found a positive interaction of information service has found larger influence among the studied farmers. Seemingly, being a part of organization farmers are often encouraged or somehow forced to maintain certain EFT interaction within the farms to maintain standard (Handschuch et al., 2013; Janssen & Swinnen, 2019), the study also found positive impacts of standardization relatively high (ON\_3). It is quite obvious that as part of organization many farmers might have to face some distinctive problems (OS\_6, OS\_9 and OS\_10) and some technical issues while if the organizational is ready to solve them and facilitate better negotiation for adopting EFT (OS\_12) the farmers likely tom adopt the EFT more confidently (G. Xu et al., 2020; Zhang et al., 2020), which is similar to our findings.

**6. Conclusion**

The general lack of spontaneous adoption of EVT among farmers has been a major concern for researchers. Several research inquiries have attempted to understand the factors impeding or facilitating the uptake of EFT and their continued utilization by farmers on a bigger scale. Research has predominantly focused on the advantages, mediating roles, and participatory roles of co-operatives and farmer’s behavioral factors affecting the adoption of modern EFT at the farm level. Moreover, prior studies mostly focused on the organizational mechanism and the effects of participation in co-operatives. Whereas, how the co-operative organizations mechanize the smooth transition of EFT among the farmers and how organizational learning, supports, and norms assist the farmers to adopt EFT has been remained unexplored. Therefore, the study utilized integrated approaches to substantially explore what extend the organizational learning, organizational norms, and support foster the adoption and how the adoption of EFT foster the smooth transition of capturing competitive advantage.

Though organizational participation on the basis of cooperative behavior has a long history, but there is a lack of research triggering the interconnection among organizational supports, organizational norms, and organizational learning. Especially, evaluating the role of organizational supports, norms, and learning within the context of farmer’s cooperatives is relatively rare. The study established a statistically viable model with the help of empirical data from 292 farmers of 38 Kiwifruit cooperative of Meixian County, Shaanxi, China. A conceptual model has been proposed, structured, and securing robustness of the model by utilizing partial least squire based SEM. The study found a significantly positive relationship between organizational supports and adoption of EFT, organizational learning and adoption of EFT, and organizational norms and adoption of EFT. The study also found organizational support, learning, and norms possessed staggering effects to foster farmer's overall knowledge, impression, and formulate a positive attitude towards EFT. Consistent with other studies, the study revealed that there is a positive interconnection between the adoption of EFT and the availing competitive advantages.

Our study comprised some distinct policy recommendations. A deeper assessment of the roles of cooperative societies in fostering the transmission of agricultural EFT will strengthen the status and implementation of policy initiatives, which is especially relevant for economies having vast, remote communities that have been characterized by small farmers, such as China. The interrelationship between environmental friendly technology and co-operative organizations in the studied regions has been found substantial; especially EFT adoption has been traced within the post-harvesting mechanism with eventually help farmers to avail better opportunity to boost the income. Kiwifruit farmers of Meixian put great emphasis on the positive effects of EFT for maintaining low production costs and economic benefits. Thus the government should provide more attention to smooth the financial access of the co-operatives. As the study found organizational norms within reactively weaker parts for fostering the adoption compare to other latent variables (supports and learning), multidisciplinary and systematic initiatives should be used as part of successful EFT promotion initiatives among kiwi farmers, with the emphasis on norms and values. Interestingly, the studied farmers have also highlighted the better opportunity of distinctive market and demands of cleaner production facilities. Therefore, the policymaker and sector should emphasize more to improve the awareness level of local people and consumers as well. In this regard, training facilities, advertisement, rewards, and better loan facilities should be avails to maintaining a smooth transition of EFT within the agriculture sectors.

The study possessed some limitations too. The first limitation is the study collected the data in a single wave. Thus, there is a profound ground to compare the impacts of the identified indicators into various regions and various time waves. Moreover, the scope and intensity of the use of certain technologies have not been quantified in our analysis, whereas overall technologies adopted by the farmers are taken into account. It will be interesting to evaluate any particular form of technology. The proposed model of the study could be elaborate for future research. First, the interaction of organizational participation can be included to measure how organizational participation can profile the behavior of farmers. Secondly, the theory of planned behavior can be used to interact with the three main latent variables (organizational supports, learning, and norms). Another research direction could be how perceived values provides by the co-operative fosters the adoption of EFT. Finally, whether the co-operative organization has any mediating role for availing new technology could be very interesting as well.

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**Table 1 Descriptive statistics of key variables.**

|  |  |  |  |
| --- | --- | --- | --- |
| **Constructs** | **Variables** | Mean | Standard deviation |
| **Organizational support** | **OS\_1** | 2.66  | 0.67 |
| **OS\_5** | 3.35 | 0.95 |
| **OS\_6** | 3.46 | 0.95 |
| **OS\_7** | 4.40 | 0.61 |
| **OS\_9** | 3.95 | 0.78 |
| **OS\_10** | 3.74 | 1.01 |
| **OS\_11** | 3.27 | 1.13 |
| **OS\_12** | 4.13 | 1.36 |
| **Organizational learning** | **OL\_2** | 3.55 | 0.89 |
| **OL\_3** | 3.56 | 0.92 |
| **OL\_5** | 3.53 | 1.03 |
| **OL\_6** | 2.17 | 1.08 |
| **OL\_7** | 3.04 | 1.24 |
| **OL\_8** | 4.36 | 0.61 |
| **OL\_9** | 4.11 | 0.69 |
| **OL\_10** | 4.42 | 0.57 |
| **Organizational norms** | **ON\_1** | 3.62 | 0.90 |
| **ON\_2** | 3.82 | 0.83 |
| **ON\_3** | 3.62 | 0.83 |
| **ON\_4** | 3.67 | 0.92 |
| **ON\_6** | 3.71 | 0.97 |
| **ON\_7** | 3.81 | 0.88 |
| **ON\_10** | 4.04 | 0.62 |
| **Adoption** | **AD\_1** | 3.87 | 0.82 |
| **AD\_2** | 4.18 | 0.79 |
| **AD\_3** | 4.03 | 0.92 |
| **Competitiveness** | **CN\_1** | 4.08 | 0.62 |
| **CN\_2** | 4.17 | 0.61 |
| **CN\_3** | 4.08 | 0.69 |
| **CN\_4** | 4.21 | 0.71 |

**Table 2 Validity of constructs (Reflective Outer Models)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Constructs** | **Variables** | **Loadings** | **Indicator****Reliability (** **λ)** | **Composite reliability** | **AVE** |
| **Organizational support** | **OS\_1** | 0.790  | 0.624  | 0.898 | 0.757 |
| **OS\_5** | 0.814 | 0.663 |
| **OS\_6** | 0.992 | 0.984 |
| **OS\_7** | 0.880 | 0.774 |
| **OS\_9** | 0.817 | 0.667 |
| **OS\_10** | 0.909 | 0.826 |
| **OS\_11** | 0.835 | 0.697 |
| **OS\_12** | 0.904 | 0.817 |
| **Organizational learning** | **OL\_2** | 0.791 | 0.626 | 0.837 | 0.771 |
| **OL\_3** | 0.892 | 0.796 |
| **OL\_5** | 0.849 | 0.721 |
| **OL\_6** | 0.923 | 0.852 |
| **OL\_7** | 0.898 | 0.806 |
| **OL\_8** | 0.873 | 0.762 |
| **OL\_9** | 0.906 | 0.821 |
| **OL\_10** | 0.884 | 0.781 |
| **Organizational norms** | **ON\_1** | 0.906 | 0.821 | 0.809 | 0.760 |
| **ON\_2** | 0.784 | 0.615 |
| **ON\_3** | 0.844 | 0.712 |
| **ON\_4** | 0.909 | 0.826 |
| **ON\_6** | 0.763 | 0.582 |
| **ON\_7** | 0.978 | 0.956 |
| **ON\_10** | 0.899 | 0.808 |
| **Adoption** | **AD\_1** | 0.896 | 0.803 | 0.904 | 0.856 |
| **AD\_2** | 0.985 | 0.970 |
| **AD\_3** | 0.891 | 0.794 |
| **Competitiveness**  | **CN\_1** | 0.870 | 0.757 | 0.835 | 0.802 |
| **CN\_2** | 0.937 | 0.878 |
| **CN\_3** | 0.867 | 0.752 |
| **CN\_4** | 0.906 | 0.821 |
| Model-fit: CFI = 0.97, TLI = 0.97, RMSEA = 0.06, SRMR = 0.06 |

**Table 3 Fornell-Larcker Criterion Analysis for Checking Discriminant Validity**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Organizational Support** | **Organizational Learning** | **Organizational Norms** | **Adoption** | **Competitive Advantage** |
| **Organizational Support** | **0.870** |  |  |  |  |
| **Organizational Learning** | 0.790 | **0.878** |  |  |  |
| **Organizational Norms** | 0.679 | 0.71 | **0.872** |  |  |
| **Adoption** | 0.574 | 0.671 | 0.703 | **0.925** |  |
| **Competitive Advantage**  | 0.503 | 0.432 | 0.568 | 0.592 | **0.896** |

**Table 4 Bootstrap results of the model (inner model)**

|  |  |
| --- | --- |
|  | **T-statistics** |
| **Adoption→ Competitive advantage** | **12.218** |
| **Organizational support→ Adoption** | **5.756** |
| **Organizational Learning → Adoption** | **4.753** |
| **Organizational Norms→ Adoption** | **4.136** |

**Table 5 Bootstrap results of the model (outer model)**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Frame/****construct** | **Indicator** | **Total sample estimate** | **Mean of sub-sample** | **Standard error** | **t-Statistics** |
| **Organizational Support** | **OS\_1** | 0.261 | 0.261 | 0.0043 | 29.129 |
| **OS\_5** | 0.246 | 0.244 | 0.0093 | 27.142 |
| **OS\_6** | 0.279 | 0.271 | 0.0031 | 22.328 |
| **OS\_7** | 0.255 | 0.245 | 0.0071 | 26.491 |
| **OS\_9** | 0.319 | 0.309 | 0.0040 | 26.189 |
| **OS\_10** | 0.302 | 0.292 | 0.0091 | 21.186 |
| **OS\_11** | 0.294 | 0.291 | 0.0102 | 17.283 |
| **OS\_12** | 0.268 | 0.268 | 0.0089 | 16.367 |
| **Organizational Learning** | **OL\_2** | 0.298 | 0.278 | 0.0099 | 13.208 |
| **OL\_3** | 0.439 | 0.409 | 0.0102 | 11.043 |
| **OL\_5** | 0.398 | 0.308 | 0.0075 | 8.233 |
| **OL\_6** | 0.358 | 0.348 | 0.0092 | 14.344 |
| **OL\_7** | 0.281 | 0.261 | 0.0087 | 11.089 |
| **OL\_8** | 0.346 | 0.336 | 0.0076 | 6.233 |
| **OL\_9** | 0.286 | 0.271 | 0.0103 | 8.123 |
| **OL\_10** | 0.357 | 0.347 | 0.0091 | 12.509 |
| **Organizational Norms** | **ON\_1** | 0.213 | 0.203 | 0.0018 | 28.754 |
| **ON\_2** | 0.409 | 0.399 | 0.0094 | 26.302 |
| **ON\_3** | 0.246 | 0.246 | 0.0031 | 29.062 |
| **ON\_4** | 0.345 | 0.342 | 0.0043 | 22.489 |
| **ON\_6** | 0.249 | 0.249 | 0.0103 | 29.830 |
| **ON\_7** | 0.366 | 0.362 | 0.0101 | 22.302 |
| **ON\_10** | 0.476 | 0.401 | 0.0528 | 21.128 |
| **Adoption** | **AD\_1** | 0.234 | 0.234 | 0.0018 | 31.038 |
| **AD\_2** | 0.345 | 0.345 | 0.0071 | 23.602 |
| **AD\_3** | 0.166 | 0.166 | 0.0031 | 21.223 |
| **Competitive advantages** | **CN\_1** | 0.419 | 0.403 | 0.0018 | 27.766 |
| **CN\_2** | 0.373 | 0.334 | 0.0071 | 29.402 |
| **CN\_3** | 0.289 | 0.289 | 0.0092 | 28.030 |
| **CN\_4** | 0.357 | 0.341 | 0.0091 | 31.089 |

**Table 6 Parameters of the structural model**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Hypothesis** | **Total sample estimate** | **Mean of sub-sample** | **Standard error** | **t-Statistics** |
| **Organizational Support-adoption** | 0.979 | 0.906 | 0.039 | 21.675 |
| **Organizational learning-adoption** |  0.714 | 0.691 | 0.066 | 9.374 |
| **Organizational norms-Adoption** | 0.803 | 0.712 | 0.049 | 8.437 |
| **Adoption-Competitive advantage** | 0.983 | 0.894 | 0.089 | 6.756 |



**Figure 1: Conceptual model**



**Figure 2 PLS-SEM results of the proposed model.**