



Research article

Smallholder decision-making process in technology adoption intention: implications for *Dipterocarpus alatus* in Northeastern Thailand

Voravee Saengavut, Norachit Jirasatthumb*

Faculty of Economics, Khon Kaen University, Thailand

ARTICLE INFO

Keywords:

Behavioral intention
SEM
Sustainable agriculture
TAM
Technology adoption

ABSTRACT

Coupled with newly introduced technology, sustainable agriculture is considered a cooperative strategy for low-income countries to improve farm productivity and economic growth. This study focuses on analyzing the process of adoption intention with a new technology associated with the use of *Dipterocarpus alatus*, a large tree species restricted to Thailand. A conceptual framework of the technology acceptance model (TAM) has been applied to explain farmers' decision-making processes. The purposive sampling approach targets farmers in the area who have *D. alatus* trees on their properties. Structural equation models, latent variables, and the hypothesized adoption intention interactions are the primary tools used in analyzing the decision-making process. Results showed that adoption intention concerning *D. alatus* technology was significantly influenced by perceived ease of use and attitudes based on experience and environmental sensibilities. This study has extended the application of TAM, providing insight into decision-making processes that are not hindered by technology implementation.

1. Introduction

Smallholders in Northeastern Thailand have been experiencing sub-standard livelihoods due to several issues. Their agricultural productivity has been relatively low compared to other regions due to lack of access to irrigation systems, adverse effects of climate change (floods and droughts) (Attavanich et al., 2019), and unstable prices for their products, all of which contribute to low incomes (Rennenberg, 2002). These circumstances create pressure on the smallholders to seek alternatives and diversify their agricultural activities. Alternatives that suit the existing ecosystem and are likely to improve their agricultural productivity are considered good options for the smallholders.

There is a large tree species, *Dipterocarpus alatus* Roxb. ex G. Don (hereafter *D. alatus*)—which is restricted to the Southeast Asian mainland and is one of the most common trees used for both timber and tapping an oleoresin—which could serve as a desirable cropping alternative. In Thailand, it is recognized as one of the most important tree species, alongside teak, because of its high value, and hence, has been the subject of afforestation programs (Boontawee, 2001). Studies have suggested that it has potential for ecosystem support, and its chemical components could be extracted for applications in the medicinal, cosmeceutical, and pharmaceutical fields (Akihisa et al., 2004; Yongram et al., 2019). Its resin can also be used as gasoline- and diesel-like fuel for engines (Suiyay

et al., 2019) and can provide benefits in support and provisioning-type services, particularly in riparian forests (Asanok et al., 2017; Kamy and Asanok, 2020). Additionally, it can provide shade for edible mushrooms (Butkhup et al., 2018; Kaewgrajang et al., 2013). Notwithstanding its economic and ecological usefulness, changing agricultural patterns in pursuit of *D. alatus* plantations as a cropping alternative cannot happen straight away. This requires approaches that encourage smallholders to adopt it as a new technology.

Adoption of suitable technology is a critical factor in promoting success in agricultural practice. In terms of economic efficiency, farmers with the intention of adopting new agricultural technology see greater opportunities for market participation (Asfaw et al., 2011) and exhibit enhanced farming precision, such as yield monitoring (Uematsu and Mishra, 2010) as well as giving rise to improved crop returns and earnings (Kariyasa and Dewi, 2013). It has also been established that technology adoption increases economic efficiency and fosters a sustainable approach, combining agriculture with conservation and agroforestry. In southern Brazil, it was noted that a farmer's desire to conserve the rainforest represented a significant willingness to embrace agroforestry technology (McGinty et al., 2008).

More than a mental attribute is required, though; studies of African farmers showed that other physical and concrete factors, including the availability of germplasm, the initial cost of agroforestry practice, and

* Corresponding author.

E-mail address: norachitji@kku.ac.th (N. Jirasatthumb).

their existing body of knowledge, all influenced adoption of agroforestry technology (Mwase et al., 2015). These cases confirmed that the factors that influence decision-making on technology adoption by farmers in developing countries are complex, involving institutional and economic factors and household demographic attributes (Mwangi and Kariuki, 2015).

The decision to adopt new technology is, therefore, an elaborate process. The technology referred to here is the process in which farmers conserve *D. alatus* and, at the same time, exploit possible benefits from it. The benefits include distilling resin from a tree to be used for diesel-fuel and extracting chemical components from leaves and barks to produce *D. alatus* soaps. Distillation of fuel requires only a little extra labor time (10–20 per tree depending how large it is) but is a bit complicated as it requires a specific machine; however, if possible, it would save farmers' cost of fuel by one-third. The average cost of soap production is about 40 baht, which can be charged at retail price at 60–80 baht per unit. Adopting this process requires a comprehensive understanding of the relevant influencing factors, especially with particular reference to NE Thai smallholder attitudes to *D. alatus* as a new agricultural alternative.

The primary objectives of this study are twofold: first, to examine farmer attitudes toward *D. alatus* innovation and the factors determining their intention to adopt the new technology; and second, to identify the relevant determinants which interact with farmer intentions to decide on new technology adoption in the future. The analysis described here was based on data collection from smallholdings in Khon Kaen province, Northeastern Thailand, as a good representative of smallholders with *D. alatus* populations. This study also contributes to the structural equation model (SEM) literature by identifying a correcting method for application to situations with small sample sizes.

The rest of this article is organized as follows: the literature, conceptual framework, and hypotheses—and their relevance to the framework—are introduced in Section 2, followed by details of the methodology, data collection, variables measurement, and statistical analysis in Section 3. In Section 4, we present the empirical results of the SEM and its effects, while in Section 5, we discuss the SEM results in the technology acceptance model (TAM), its direction, policy implications, and conclusions.

2. Literature review and conceptual framework

Technology adoption research distinguishes between *ex-post* and *ex-ante* studies. *Ex-post* technology adoption studies investigate the motives or reasons that have encouraged or even stimulated farmers into adopting a technology. In contrast, *ex-ante* studies demonstrate acceptance of new technology prior to its use in practice. These two groups provide information differently at the decision-making stage of an adoption process (Pierpaoli et al., 2013). In the work described here, we focused on the context of introducing new technologies to farmers before actual practice.

The core construct addressed in technology adoption literature emphasizes a process of decision-making, particularly the influencing factors that drive attitudes toward an intention to adopt innovation. Related work has recognized that the complexity of new technologies, their compatibility, and their relative advantages, as perceived by individuals, affects the degree of innovation adoption (Rogers, 1983).

Nowadays, there is a significant body of work on attitudes showing that technology adoption has a foundation in the TAM proposed by Davis (1989). Early in its adoption, TAM was used to explain computer usage in information technologies, based on attitudes toward technologies. The TAM has a theoretical grounding in Theory Reasoned Action (TRA), which stated that individual beliefs influence attitudes. As a revised version of TRA, the Theory of Planned Behavior (TPB) demonstrates that behavioral intention is the best predictor of behavior, as captured by attitudes, subjective norms, and perceived behavioral control constructs (Fishbein and Ajzen, 1975). The TAM applies these underlying concepts to delineate linkages between attitudinal components, perceived ease of

use (PEOU), and perceived usefulness (PU), to determine user attitudes concerning technology adoption intentions.

The decision-making process used for adopting agriculture innovation by farmers in developing economies involves more complex situations. Such decision-making translates into action, based on intrinsic and extrinsic factors (Meijer et al., 2015).

In the following section, the conceptual framework of farmer attitudes related to the intended adoption of *D. alatus* technologies, especially the main variables and their relationships, is discussed. Endogenous variables, attitude, and adoption intention is discussed first, followed by consideration of exogenous variables.

2.1. Endogenous variables: attitude and adoption intention

2.1.1. Attitude toward technology adoption intention

In the sustainable agriculture literature relating to practices and technology, farmer attitudes play a vital role in the decision-making process associated with technology adoption. Willock et al. (1999) defined attitudes as a positive or negative reaction in relation to judgment about an object, whether the object was a person, an idea, or a physical object. These evaluated perceptions, either for or against, influenced farmer behaviors (Rehman, 2000). When farmers receive information about a new agricultural opportunity, technical information forms the basis of the perceptions and attitudes developed toward the technology at the early phase of the decision-making process.

In a socio-psychology model, attitudinal behaviors are often investigated using other intrinsic variables. In the TPB model, in addition to attitude being a subjective norm, perceived behavioral control makes up the other main component in predicting behavioral intention. However, in an agricultural context, just what makes the greater impact on behavior intention is subject to debate, as various researchers have studied just which variables should be considered and what their effects were. Attitude was seen as significant in explaining farmer intentions in adopting sustainable agricultural practice (Akyüz and Theuvsen, 2020), while perceived behavioral controls were shown to be invalid (Yazdanpanah et al., 2014).

In our context, farmers were considered to have been informed about technical innovation by field demonstrations prior to actual usage. Attitudes toward use, which in this context refers to the prospective farmers' positive or negative feelings about adopting *D. alatus* technologies, were perceived to be at the center of the analytical framework used to predict adoption intention. Therefore, we hypothesize that a positive attitude toward agricultural innovation will increase the likelihood of adoption, and vice versa (H1). The perception of the environmental benefit of using technology has a positive effect on farmer attitudes.

In light of the preceding, a stand-alone theory in the analysis could not provide a holistic picture of pre-adoption processes. Hence, we turned to the *ex-ante* technology adoption model to identify determinants in the decision-making processes. According to TAM, the perceptual aspect of human behavior is a core construct in this approach to explaining technology innovation adoption. Regarding this approach, the direction framework emphasizes the linkage between perception and attitude to adoption intention with respect to using new technology (Pierpaoli et al., 2013).

2.1.2. Perceived ease of use

It has been reported that perception regarding technology innovation is a contingent construct that determines adoption intention to use technology and has a relationship with socio-demographic factors (Pierpaoli et al., 2013). Individual perceptions influence the uptake of agricultural innovation (Adrian et al., 2005), with the ease with which new technology can be used as a crucial feature (Rezaei-Moghaddam and Salehi, 2010). In TAM, both PEOU and PU are distinct constructs that have been proposed in the prediction of user attitudes toward the adoption and use of technology. Davis (1989) defined PEOU as the belief that using a particular product or service would be free of physical and

mental effort and had PU—which refers to the belief that using a specific system would enhance work performance.

Empirical studies have found that PEOU influences PU, since, if the technology is easy to apply, it will be considered more useful (Schaak and Mußhoff, 2018; Wu and Wang, 2005). Research in agricultural technology has found that attitude needed to be addressed to facilitate the uptake of agricultural technology and revealed that PEOU was antecedent to (Verma and Sinha, 2018).

Research has also suggested that PEOU is a stronger influence than PU on attitudes to the adoption of agriculture technology in rural China (Li et al., 2007). To some extent, although PEOU exerts an indirect influence on individual acceptance of technology (Lui and Jamieson, 2003), the direct effect of PEOU on adoption and usage behavior has been shown as being more influential than its indirect effect (Szajna, 1996).

In our study, the aim was to evaluate the forces behind the adoption of *D. alatus* technology. Thus, the PEOU effect on farmer attitudes and adoption intention were combined to determine possible relationships between the two constructs while simultaneously providing a more in-depth examination of the subject of *D. alatus* technology adoption. Based on the above definitions, we hypothesized that PEOU positively and directly affects attitude (H2) and adoption intention toward using *D. alatus* technology (H3).

2.2. Exogenous variables

Control variables for attitude and intention to adopt innovation include socio-demographic factors, farmer characteristics, financial resources, and the relevant production costs (see Jones and Dunlap, 1992; Pierpaoli et al., 2013). Regarding the literature review findings, we discuss the rationale behind and include three explanatory variables into the conceptual model as well as develop hypotheses regarding their effects.

2.2.1. Age

It is possible that younger householders were more willing than older ones to take risks and were more likely to adopt agroforestry technologies (Thangata and Alavalapati, 2003). Evidence from a study on agroforestry technologies by Gyau et al. (2014) confirmed that two extreme farmer age groups, the very young and the very old, were more likely to adopt new approaches in cocoa agroforestry. Considering this evidence and the fact that the average age of sample is in elderly range (60.92 see Table 2), we hypothesized that the household leader age negatively affected adoption intention (H4)¹.

2.2.2. Cost of implementation

It has been proposed that the decision on whether to adopt new technology is a choice resulting from a comparison of uncertain adoption benefits and costs (Hall and Khan, 2002). A net gain from adoption, accounting for all the costs associated with using the new technology, is a critical determinant in the adoption process, especially for farmers in developing economies (Foster and Rosenzweig, 2010).

According to Vanclay (1992), two parts of the implementation cost are considered—the capital spending on the innovation itself and the resources required by farmers to forego income until the new system generates it. Intellectual cost is another aspect where farming strategies and practices require knowledge of modern agriculture, to the extent that individual farmers may have to learn new methods of performing tasks to modify their operations.

The capital cost of implementing technology has been found to impede agriculture technology uptake. For instance, it was found that a

¹ There is also the case that age could have a quadratic relationship to adoption. Positive influence would continue to some certain age, then become negative (which normally happens in elderly people). In this study, participants are elderly, so the assumption of negative relationship is sensible.

drop in subsidies for seed and fertilizers hindered African farmers in conservation practice uptake (Muzari et al., 2012), while Li et al. (2007) found that the cost of technology exerted a negative influence on attitude and the adoption of mobile-commerce in a rural area of China. Hence, in this study, we hypothesized that the implementation cost of *D. alatus* technology would have a negative relationship with adoption intention (H5).

2.2.3. Experience and farmer characteristics

The role of experience as a personal factor is based on social background and individual value-forming attitudes as well as assessment processes as part of decision-making (Prager, 2011). Evidence has supported the positive influence of farming experience on professional perceptions of organic farming and the expectation that the adoption of organic agriculture would diffuse through the farming community (Wheeler, 2008). Moreover, farmer expertise provides a practical tool for them to distinguish between current and new technology and has thus been considered as a factor weighing down the adoption level (Hussain et al., 2009). Since we investigated the decision-making process in adopting *D. alatus* technology before its actual use, a farmer who gained a trial opportunity from the agricultural extension system was assumed to be open-minded about new technology, to the extent that such an experience could function as a proxy for actual farming experience. In this study, we therefore hypothesized that farmers with previous agricultural training experience would have positive attitudes toward *D. alatus* technology (H6).

2.2.4. Environmental views in relation to sustainable agriculture

An environmental perspective has been considered to describe farmer views toward environment quality and conservation attitudes, conservation beliefs, and ecological worldviews (Henning et al., 2012) and appears to reflect their perceptions of environmental problems, given their farming practices (Ervin and Ervin, 1982). A paradigm of attitudes in a concept of alternative-conventional agriculture (Beus and Dunlap, 1991), stated that a farmer's willingness to commit to either an alternative or a conventional agriculture system was related to their perspectives on the environmental impacts caused by agriculture practices (Thompson et al., 2015).

Since the *D. alatus* technology, as developed, underlined the philosophy of conservation and sustainable agriculture, we sought to determine whether farmers' views on the environment would stimulate their attitude to *D. alatus* technology and later have an indirect effect on adoption intention. However, we did not aim to test the validity of an environmental measurement construct in our work, although farmer participants were asked if they thought processing *D. alatus* products yielded environmental benefits, especially for *D. alatus* conservation. We hypothesized that farmers' views on the environment positively affected their attitude toward using *D. alatus* technology (H7).

The conceptual framework outlined above has been presented in Figure 1. The hypotheses derived from the theoretical model and descriptions of the relevant latent variables have been summarized in Table 1.

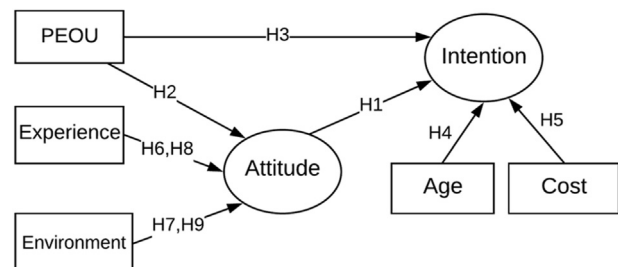


Figure 1. The conceptual model and variable constructs on *D. Alatus* adoption.

Table 1. Definition and explanation of terms and latent variables in the conceptual framework.

Hypothesis	Description
H1	Attitude has a positive direct effect on the intention to adopt <i>D. alatus</i> technologies
H2	PEOU regarding <i>D. alatus</i> technologies has a positive direct effect on attitude
H3	PEOU has a positive direct effect on the intention to adopt <i>D. alatus</i> technologies
H4	Household leader age has a negative direct effect on adoption intention
H5	Implementation cost has a negative direct relationship to adoption intention
H6	Experience has a positive direct effect on attitude toward <i>D. alatus</i> technologies
H7	Environmental attitude has a positive direct effect on attitude to using <i>D. alatus</i> technologies
H8	Experience has a positive indirect effect on adoption intention
H9	Environmental views have a positive indirect effect on adoption intention

We suggest that the identified exogenous latent variables and the following hypotheses were proposed following a conceptual framework based on previous literature.

3. Methodology: the SEM with latent variables

The model presented in the conceptual framework (Figure 1) could be described as an SEM with latent variables. In addition to a typical SEM analysis, the interactions of intention to adopt technology were examined. Here we have first explained the critical elements involved and the notion of a latent variable SEM (Bayard and Jolly, 2007; Kenny, 2011; Weston and Gore, 2006).

3.1. Sampling and procedures

A purposive sampling technique was used to select farmers to participate in this study. Technology adoption restrictions were constrained by study-specific characteristics, including technical capability and *D. alatus* tree availability on a farm owned by the potential participant. The main selection criteria included having at least twenty 5–10-year-old *D. alatus* trees on the farm and a resident who currently owned the property. The screening process resulted in a total of 80 participants being selected². A semi-structured interview was used to elicit information from participants regarding new technology adoption, after a couple of focus groups had been used to develop the survey instrument. The survey was designed to elicit how farmers understand the pros and cons relevant to *D. alatus* trees, the technology used on farms, and innovation expectations. The critical components regarding the TAM are based on the previous literature (Rezaei-Moghaddam and Salehi, 2010; Pierpaoli et al., 2013; Zeweld et al., 2017). The survey instrument included questions regarding five steps associated with the technology adoption process, perceptions related to *D. alatus* beneficiaries, and demographics. The interviewers received prior training concerning survey instructions and research protocol. A pre-test was carried out before applying the survey to local farmers, and niche specialists were used to analyze how questions could be interpreted. Based on the feedback during a pilot test, the final version of the survey instrument was developed for data collection. Data were collected for two rounds of interviews conducted in the middle of the 2018 growing season. Each interview took approximately 20 min and was conducted face-to-face with the subjects in Thai. Data was numerically coded for each question and entered into a spreadsheet for further statistical analysis. Among qualified farmer

² This number of participants was not according to the general “rules of thumb” which require a large sample size. However, this large size is not always decisive. Bentler and Chou (1987) suggested that a ratio of observations to estimated parameters in SEM model could be low as 5:1. Jackson (2003) further asserted that the adequacy of sample size varies because of factors such as, indicator’s reliability, relationships among selected variables, etc. The model in this study comprises two latent variables and five explanatory variables with 80 observations, meaning that the ratio is about 8:1 which is acceptable.

participants in the study area, 13 farmers who participated in the pre-test were excluded from the final study. Since the samples were purposively selected due to the limited suitable samples in a small population, the survey response rate was very high, nearly 70 percent. There were no missing data, and there were a total of 47 farmer samples for data analysis. STATA 15 software was used for data management and to analyze the structural model.

3.2. Variables measurement

In the measurement model, the two latent constructs used in this study, *Attitude* and *Adoption intention*, supported the hypothesized constructs. Attitudes toward *D. alatus*, considering its benefits, applications, and potential technology adoption, were indicated using item-by-item measurement. The item statements used in the questions were measured using a seven-point Likert Scale, ranging from 1 “strongly disagree” to 7 “strongly agree.” The statements measured for latent variables were derived from prior farmer adoption studies and adoption decision theory. The questions, statements, scales, and the exogenous variables used in the measurement model have been presented in Table A1.

3.3. Estimation

SEM is similar in several ways to correlation multiple regression analysis, except that it is used to calculate and analyze variance. There is a combination of two movement components in SEM—factor analysis and path analysis.

Factor analysis, known as *the measurement model*, captures relationships between observed variables (instruments) and their corresponding latent variables. The measurement model for exogenous and endogenous variables can be seen in Eqs. (1) and (2), respectively.

$$y = \Lambda_y \eta + \varepsilon \quad (1)$$

$$x = \Lambda_x \xi + \delta \quad (2)$$

where y refers to a $p \times 1$ vector of observed endogenous variables, and x represents a $q \times 1$ vector of observed exogenous variables. Λ_x denotes the $q \times n$ matrix of regression coefficients of x on ξ , while Λ_y represents the $p \times m$ matrix of regression coefficients of y on η (or loadings). Symbol η denotes an $n \times 1$ random vector of latent endogenous variables, while ξ indicates an $m \times 1$ vector of latent exogenous variables. Finally, ε and δ indicate $p \times 1$ and $q \times 1$ vectors of the measurement errors in y and x , respectively. Since the empirical analysis in this study was conducted in terms of standardized variables and beta coefficients, the intercept terms in these two equations were estimated at the latent variables’ mean values.

The path analysis, also referring to the structural model, captures interrelationships among constructs. The analysis considers measurement and structural models simultaneously to represent a full structural model or composite model. Using a covariance matrix, a structural model

was used to estimate the causal relationships between latent variables, as indicated in the conceptual model. The structural model can be represented in Eq. (3):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

where η and ξ are as defined for Eqs. (1) and (2), and B stands for the $m \times m$ matrix of coefficients, with β_{ij} representing the effect of the j^{th} endogenous latent variable on the i^{th} endogenous latent variable; Γ represents the $m \times n$ matrix of the vector of disturbances (ζ). This assumes that the unique factors (ε and δ) have expected values of zero, have covariance matrices of the exogenous latent variables ($\Sigma_{\xi\xi}$) and covariance matrices of equation disturbance ($\Sigma_{\zeta\zeta}$), and are uncorrelated with either each other, or with ξ and ζ (Bollen and Noble, 2011).

Eqs. (1), (2), and (3) illustrate a general form of the model framework. A two-step approach was performed first to assess the measurement model and then to examine the hypotheses by testing the structural model. First, confirmatory factor analysis (CFA) was applied to obtain a satisfactory measurement model, using Eq. (2). The estimated variance of indicators accounted for the latent construct is assessed by the factor loadings—the higher the factor loadings of indicators present, the higher the strength of convergent validity in theoretical similarity. Then, after we had obtained a valid measurement model, path analysis in the structural model was used to examine the hypotheses underlying the relationships among latent variables, based on the literature. In line with published work (Tang et al., 2013), the estimation procedure was used to verify a decision process (Zeweld et al., 2017) and investigate the factors that influenced farmer intention behaviors. We assumed that the latent variables were proportional to a linear combination of the observed indicators relating to the latent variables. The estimation of variable path coefficients for adoption intention presented a direct (or indirect) linear function of the derived latent variables.

In this study, the conceptual model in Figure 1 represents the estimation procedure in Eqs. (1), (2), and (3). In the measurement model, observations were applied first in Eq. (4), with *Attitude* (η_1) and *Adoption intention* (η_2) representing the observed endogenous variables presented in Eq. (4). Since the latent variable was unobservable, and therefore had no measurement, one coefficient was fixed at 1, namely *Attitude1* and *Adopt1*, to assign the measurement scale. Thus, *Attitude* was measured on the same scale as *Attitude1*, and similarly for *Adoption*. Next, in Eq. (5), the error terms of the latent variables were fixed at zero. SEM estimation then followed, via Eqs. (4), (5), and (6).

$$\begin{bmatrix} \textit{Attitude1} \\ \textit{Attitude2} \\ \textit{Attitude3} \\ \textit{Intention1} \\ \textit{Intention2} \\ \textit{Intention3} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \lambda_{2,1} & 0 \\ \lambda_{3,1} & 0 \\ 0 & 1 \\ 0 & \lambda_{5,2} \\ 0 & \lambda_{6,2} \end{bmatrix} \begin{bmatrix} \textit{Attitude} \\ \textit{Intention} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} \textit{Age} \\ \textit{Cost} \\ \textit{Experience} \\ \textit{Environment} \\ \textit{PEOU} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \textit{Age} \\ \textit{Cost} \\ \textit{Experience} \\ \textit{Environment} \\ \textit{PEOU} \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} \textit{Attitude} \\ \textit{Intention} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ \beta_{2,1} & 0 \end{bmatrix} \begin{bmatrix} \textit{Attitude} \\ \textit{Intention} \end{bmatrix} + \begin{bmatrix} 0 & 0 & \gamma_{1,3} & \gamma_{1,4} & \gamma_{1,5} \\ \gamma_{2,1} & \gamma_{2,2} & 0 & 0 & \gamma_{1,5} \end{bmatrix} \times \begin{bmatrix} \textit{Age} \\ \textit{Cost} \\ \textit{Experience} \\ \textit{Environment} \\ \textit{PEOU} \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \end{bmatrix} \tag{6}$$

Structural model goodness-of-fit (GOF) statistics evaluate model fit, in terms of: a) the significance of the estimated parameters; b) the variance

of the observed and latent variables; and c) the overall model fit with the observed data, based on model fit indices (Weston and Gore, 2006). We applied the latest current fit indices, as used by most software programs.

Additionally, the size of the samples is also in need of technical discussion here. Typically, the maximum likelihood in typical SEM estimation requires a large sample size to achieve the best fitting in terms of the fit index value. This estimation assumes multivariate normality (Jöreskog, 1970; Podsakoff et al., 2006), but this is not the case in this study as its sample size is small ($n < 100$). This small size could be problematic, especially the likelihood ratio test statistics and other fit-indices that would incline toward non-rejection of an unacceptable model (Jiang and Yuan, 2017). The dependency of fit index calculation on sample size has been well recognized (Bollen, 1990), and there are several procedures to improve the approximation of the likelihood ratio test, including the Bartlett, Yuan, and Swain corrections (Antonakis, 2013). This study remedies the issue of sample size by applying Swain (1975) to correct Chi-square statistics. GOF statistics and relative fit indices for small sample size are indicated by the Bollen Incremental Fit Index (IFI) and the Tucker–Lewis Index (TLI), which are unaffected by sample size (Dillon et al., 1996; Hu and Bentler, 1995; Marsh et al., 1988). Thus, Swain's corrections have been reported as providing robust estimators and incremental model fit (Herzog and Boomsma, 2009).

4. Empirical results

In this section, survey results, descriptive statistics, and SEM estimation have been discussed.

4.1. Survey results and descriptive statistics

The field survey was carried out in northern Khon Kaen province, Thailand, where land in the NE region is generally arid, with a long dry season. The typical vegetation consists of stunted trees and sparse grass, resulting in poor farming conditions. The study area covered several villages with a reasonably well-distributed *D. alatus* forest community of >70 mature trees (sizes ranged up to 3–4 diameters, and trees were >10 years old). *D. alatus* trees are naturally grown in open paddy, flat plain fields (paddy field), or near canals, and in this NE region, a tree community of this size was considered relatively large.

Descriptive statistics for the representative farmers have been listed in Table 2. Farmer socio-demographic characteristics—that they were 60 years old, on average, had finished their education to at least high school level, and had an average of five people in their families—were in line with the regional population characteristics (census). On average, the participants owned 11 rai of land and rented a further two (a rai is a Thai land area unit of 1,600 m²). A typical representative farmer earned an off-farm income ten times higher than his on-farm income. However, these two income sources typically did not offset farming expenditure in one cropping season, and the respondents relied very much on the government bank and village funds for loans. The participants grew multiple crops, including rice, sugarcane, and green-leaf vegetables. Some hardwood tree species were found on the land, such as *D. alatus*, teak, and others. Farmer representatives had received, on average, two government agricultural extension training experiences in the last year.

The confirmatory factor analysis was carried out for a satisfactory measurement model by evaluating the reliability and validity of the constructs. All thresholds were based on Fornell and Larcker (1981) and Hair et al. (2010). To test the reliability, the individual item met the relevant criteria of composite reliability (CR) and Cronbach's alpha (>0.7). The reliability test indicates the acceptable internal consistency of a set of variables. The Cronbach's alpha statistic is measured the inter-item-correlation for all pairs of variables on a scale. Statements on each observed item in the latent constructs. The *Attitude* construct consisted of three observed variables related to the potential of *D. alatus* benefits to farmers ($\alpha = 0.776$), and these three items fit well as the latent attitude factors (above 0.45). For the construct of behavioral

Table 2. Descriptive statistics for the observed exogenous variables (n = 47).

Variables	Min.	Max.	Mean	SD.
Age (years)	33	90	60.91	9.39
Education (years)	1	23	6.57	4.16
Farm income (TH Baht/rai)	0	20,500	4,432	4,313
Non-farm income (TH Baht)	0	250,000	43,866	43,866
Expenditure	0	15,000	2,027	2,534
Experience	0	15	1.723	2.447

Note: Age is measured as the head of household's age. Education is measured as the number of years of schooling of the head of household. Family-size is measured as the number of members of >18 years of age. Farm income is estimated based on average annual farm income in Thai Baht (1 USD ≈33 Thai Baht) per rai (1 rai = 0.16 ha). Non-farm income is measured based on average off-farm income per year in Thai Baht. Expenditure is measured based on all annual spending related to farm practices per rai. Experience is measured based on the frequency of attending the agricultural training held by government agencies in the past few years.

intention to adopt, three observed items measured farmers' intention to apply technologies in the next year ($\alpha = 0.966$). All three items had factor loadings above 0.85 for the adoption construct. Thus, the reliability analysis suggested that the indicators for both latent constructs were highly satisfied.

The convergent validity measures a level of coherency across the indicators within each construct. We assessed through the standardized factor loadings and average variance extracted (AVE). The results show the estimates loading and AVE were considered acceptable (>0.5). All factor loadings were significant ($p < 0.001$) and higher than 0.5 (Awang et al., 2015). The standardized factor loadings were statistically significant in both models, at the critical 5% level, and their coefficients were similar in magnitude. The minimum factor loading was 0.589, which was above the recommended level (Jöreskog et al., 2001). In explaining this, it was noted that, from Table 2, Attitude2 was the most critical indicator of Attitude, while Attitude1 and Attitude3 were the weakest. For Intention, Intention1 and Intention2 were the most reliable indicators in the model, while Intention3 presented a negative coefficient, even though it was a statistically significant component. The discriminant validity was examined whether the AVE value of a latent construct is more extensive than its squared correlation (SC). If so, it indicates that each construct shared more variance with its associated indicators than with any other latent variable (Mehmetoglu, 2015). As a result, AVE values were higher than the SC value (=0.076), thereby indicating an acceptable discriminant of the model. Hence, the measurement model in this study was valid and reliable. Table 3 below displays properties required for model validity. Additionally, Table A2 (in appendix) shows the goodness-of-fit indices show that the measurement model had a satisfactory fit.

4.2. The estimated SEM

This estimation shows the relationships between the Attitude and Adoption intention constructs for farmers toward *D. alatus* technology and has been followed by examining whether the observed exogenous variables influenced the latent constructs. Note that maximum likelihood (ML) estimation requires a large sample and that the normality assumption in the covariance structure analysis provided the smallest

possible standard errors—although the standard errors and the GOF may be misleading due to normality assumption violations.

Addressing small samples and non-normality in linear SEM can achieve a consistent ML estimator. The Satorra–Bentler (SB) adjustment is used to rescale Chi-square tests for model GOF (Satorra and Bentler, 1994) and was obtained in our work by using the built-in function in the STATA15 software. The GOF statistics of the measurement model measure in terms of conventional fit indices, which include Chi-square (χ^2), the comparative fit index (CFI), the root mean square error of approximation (RMSEA) (measuring the 90% confidence interval), and the standardized root mean square residual (SRMR). Since normality violation and small sample size affected the validity of the fit indices, relative fit indices—including the Bollen IFI, and the Tucker–Lewis index (TLI), or the non-normed fit index (NNFI)—were preferred, instead of conventional indices. The Swain correction, scaling factor, and converging to one asymptotically were multiplied by the Chi-square statistic, resulting in a better Type 1 error approximation (Herzog and Boomsma, 2009).

A wide range of cut-offs for levels of GOF indices was available; hence, the rule of thumb applied was based on Kline (2015). The acceptable cut-off model fit was indicated when the CFI and IFI were >0.90, by a TLI >0.95, and an RMSEA and SRMR <0.08. As a result, conventional measurement validity indicated that the model did not fit the data very well (i.e., with respect to χ^2 , RMSEA, SRMR).

The χ^2 statistics were used to assess overall fit and reflected the distance between the sample covariance and fitted covariance matrices. In other words, the higher the χ^2 p-values, the better the overall GOF. The χ^2 value was 77.030 (df = 30), indicating a weak GOF for the model; however, it has been reported that the χ^2 statistic is sensitive to deviations from normality and that sample sizes <400 usually result in low p-values (Hox and Bechger, 1998).

The relevant relative fit indices preferred for this study, including CFI, TLI, IFI, and SRMR (Kline, 2015), were used to evaluate the model fit and improve Swain rescaling. Overall, the results indicated that the proposed model performed well, with the GOF (with SB adjustment) and the Swain–SB corrections for the model presented in Table A2 (note that the Swain–SB correction does not provide IFI or SRMR indices).

We then reviewed the estimated structural model and tested the previously listed hypotheses, based on the attitude and behavioral

Table 3. Reliability of individual items, convergent validity, and discriminant validity of measurement model.

Constructs	Items	Factor loadings ^a	S.E.	R ²	Cronbach's alpha	CR	AVE
Attitude	Attitude1	0.776***	0.069	0.603	0.776	0.820	0.609
	Attitude2	0.818***	0.111	0.669			
	Attitude3	0.730***	0.097	0.533			
Intention	Intention1	0.998***	0.003	0.999	0.966	0.969	0.911
	Intention2	0.995***	0.006	0.991			
	Intention3	0.866***	0.059	0.736			

Note:*** $p < 0.001$, ^astandardized loadings, Composite Reliability (CR), Average Variance Extracted (AVE).

intention constructs present in Table 4. The R^2 indicated that the available variances for *Attitude* and *Intention* had captured approximately 52% and 58%, respectively. It was also seen that the coefficient determinant presented plausibly well for the full model with the exogenous variables, and with their inclusion, the R^2 was raised to 78%. Overall, the coefficients were in line, in terms of sign and significant relationships, indicating that, as hypothesized in the conceptual model, the findings confirmed that *Attitude* was an antecedent for behavioral intention (*Intention*).

A strongly positive *Attitude* affected farmers' intention to adopt *alatus* technologies, and indicated that attitude toward *D. alatus* technology was a prerequisite for raising the level of behavioral intention. At the same time, PEOU was confirmed in its relationship to adoption intention; hence, the fact that PEOU was strongly positive to *Intention* supported H3. On the other hand, H2 was not supported, as PEOU showed a negative association with *Attitude*. These results implied that farmers did not see *D. alatus* technologies as easy to use, although they were still willing to use them. Its indirect effect on *Intention*, however, was negligible and insignificant.

Regarding exogenous variables, H4 was supported, showing that the impact of *Age* was negatively significant. The coefficient of -0.018 supported the hypothesis that younger farmers tended to adopt new technologies and that adoption intention tended to fall with increasing age. It was also clear that, in contrast to our expectation, H5 was not supported, as *Cost* significantly and positively affected *Intention*, and that the implementation cost of *D. alatus* technology was not obstructing farmers' intention to use it (this has been discussed further later).

The findings supported H6, suggesting that the more training farmers experienced through extension services, the more positive attitude they would have. The indirect effect of *Experience* on *Intention* was positively significant. Finally, the results supported H7, showing that environmental view had the most substantial effect (coefficient = 0.72) on attitude. This suggested that farmer environmental views directly and powerfully affected their attitudes and indirectly affected farmers' intention to adopt technologies, as proposed in H9.

The standardized indirect and total effects on *Attitude* and *Intention* associated with each variable illustrated the strength of causal relationships in the model. Overall, the total effect is the sum of the direct and indirect effects of a given and is called the effect coefficient. A direct effect is the effect of a causal variable on an endogenous variable, while an indirect effect is the effect of a variable on an endogenous variable that has been intervened or mediated through other variables in the model. In other words, the magnitude of the indirect effect reflects the amount of mediation through the relevant mediator variable. Here, for example, PEOU, *Experience*, or *Environment* pass through *Attitude* on then move on to *Intention*.

PEOU was the variable with the largest effect on *Intention*, with a result of 0.618, followed by *Attitude*, *Environment*, and *Cost*, with total effects of 0.34, 0.24, and 0.193, respectively. Although no direct causal relationship was established, the impact of *Environment* on *Intention* was significant, passing through *Attitude*. *Experience* had a small but significant effect on *Intention*, with a total effect of 0.041. Finally, *Age* had a weakly negative and insignificant effect on *Intention*, while *Cost* was found to have an unexpectedly positive causal relationship with intention, with a total effect of 0.193.

5. Discussion and conclusion

In this study, we examined how socio-economic and psychological factors affected smallholders' intentions to adopt new technologies for conserving and using *Dipterocarpus alatus* in NE Thailand. SEM was applied based on the TAM, to form the latent variables needed to estimate direct influences on the intention to adopt the new technology.

The findings revealed that positive relationships between psychological factors led to a strong intention to adopt the new technologies, supporting hypothesis H1. PEOU also positively contributed to the intention to adopt *D. alatus* innovations, supporting hypothesis H3. The strong impact of PEOU on farmers' intentions was consistent with previous findings that when technologies were perceived to be "non-difficult," there was a high probability of acceptance. This applied regardless

Table 4. Results for hypotheses paths and the structural model (standardized coefficients)^a.

Hypotheses	Paths	Coefficients	Results
<i>Direct effects</i>			
H1	Attitude → Intention	0.340 (0.095)***	Supported
H2	PEOU → Attitude	-0.154 (0.077)*	Not Supported
H3	PEOU → Intention	0.670 (0.055)***	Supported
H4	Age → Intention	-0.018 (0.070) **	Supported
H5	Cost → Intention	0.194 (0.096)	Not supported
H6	Experience → Attitude	0.122 (0.078)**	Supported
H7	Environment → Attitude	0.714 (0.094)***	Supported
<i>Indirect effects</i>			
H8	Experience → Intention	0.041 (0.026)**	Supported
H9	Environment → Intention	0.240 (0.116)**	Supported
	PEOU → Intention	-0.052 (0.055)	
<i>Total effects</i>			
	Attitude → Intention	0.340 (0.095)***	
	PEOU → Intention	0.618 (0.160)***	
	Age → Intention	-0.018(0.025)	
	Cost → Intention	0.193(0.137)**	
	Experience → Intention	0.041(0.028) **	
	Environment → Intention	0.240 (0.116)**	
	PEOU → Attitude	-0.154 (0.077)*	
	Experience → Attitude	0.122 (0.036)**	
	Environment → Attitude	0.714 (0.094)***	

R^2 : Attitude = 0.524, Intention = 0.578, Overall = 0.782

^a Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

of how the technologies were to be used or the objective for using them, such as for mobile applications (Verma and Sinha, 2017), precision agriculture (Adrian et al., 2005; Rezaei-Moghaddam and Salehi, 2010), or sustainable agriculture (Zeweld et al., 2017).

We also confirmed published findings that a significant relationship between attitude and intention to adopt supported a positive attitude, which encouraged new technology adoption. This positive attitude reflected an awareness of the benefit to be achieved by practicing a new agriculture technology and was also similar to other findings, such as those concerning the integration of tree species into cocoa agroforestry systems (Gyau et al., 2014), and applications that improved grassland management in Mexico (Martínez et al., 2013).

We noted that the direct effect between PEOU and farmer attitudes did not support hypothesis H2. This could be interpreted as indicating that a positive attitude toward conserving and utilizing *D. alatus* was based more on experience (H6 and H8) and concern for the environment (H7 and H9), rather than merely on PEOU itself.

In a related outcome, strong positive causation of environmental benefits on the intention to adopt *D. alatus* technologies (via attitude attributes) implied that it was important to help farmers recognize the environmental benefits, allowing them to engage with a new technology with the conscious intention of conserving either a rural landscape or water quality (Thompson et al., 2015). In this study, research participants expressed their will to use *D. alatus* technologies in the future, believing that the technologies were environmentally friendly.

It was also found that the direct effect of technology costs appeared to be counter-intuitive to the adoption intention (H5), with high cost apparently leading to an acceptance of adoption. This result suggested that the government always promoted agricultural alternatives in this area through the use of subsidies. Thus, high cost was not a hindrance to farmers' intention to adopt *D. alatus*, as they anticipated that adoption would be supported by government subsidy. Similar evidence had been previously reported as revealing the direct success of subsidies, in the form of soft loans or green carbon credits, in covering the household expenses and farming costs involved in switching to organic practices (Achavanuntakul and Panyakul, 2016). In our case, farmers would like to participate without worrying about production cost and were likely to do so if a government support program was available.

The results also showed that age did not significantly affect the intention to adopt (H4). This implied that our hypothesis that the older the farmer, the more accepting they were of new technologies was incorrect.

In conclusion, this study has demonstrated the existence of farmer intentions to adopt *D. alatus* technologies for sustainability, has identified associated causal mechanisms, and has produced three policy lessons.

First, it was apparent that socio-psychological factors played a significant role in farmer decision-making concerning sustainable practices.

This implied that a long-term policy directed toward creating positive attitudes toward innovation would be an important foundation for the uptake of sustainable *D. alatus* agriculture in the future. Second, policy-makers must help farmers acknowledge the various benefits of *D. alatus*, as this would encourage them to adopt a role in conserving and utilizing *D. alatus*, as an alternative form of farm-income. Third, local financial support would be critical in inducing farmers to adopt *D. alatus* technologies. However, before implementing this, a survey on how farmers would receive subsidies should be taken so that the government could design an appropriate package.

By applying these policies in combination, we believe that conservation of plant genetic resources, using the example of *D. alatus* in this study, could be integrated into a rural development program.

In short, this study has revealed the existence of farmer intentions to adopt *D. alatus* technologies for sustainability, together with associated causal mechanisms. We hope that the positive outcomes from our work can be a small force supporting the global agendas relating to sustainable agroforestry and biodiversity protection.

Declarations

Author contribution statement

Voravee Saengavut: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Norachit Jirasathumb: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Funding statement

This study was supported by Research and Technology Transfer Affairs of Khon Kaen University (Project ID: KKU-YN2561-004).

Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Appendix

Table A1. Statements and scales used in the measurement model, which represent the *Attitude* and *Adoption* constructs.

Indicators	Statements	Scale (1–7)
Indicators represent the <i>Attitude</i> and <i>Adoption</i> constructs.		
<i>Attitude1</i>	Growing <i>D. alatus</i> trees helps maintain the quality of soil nutrients.	Strongly disagree to strongly agree
<i>Attitude2</i>	The innovation of <i>D. alatus</i> technology helps improve the quality of <i>D. alatus</i> -based products.	Strongly disagree to strongly agree
<i>Attitude3</i>	Technology developed for <i>D. alatus</i> application can be used practically.	Strongly disagree to strongly agree
<i>Adopt1</i>	Applying drill and pipes to obtain <i>D. alatus</i> resin is my main interest of accepting <i>D. alatus</i> technology in the future.	Unlikely – very likely
<i>Adopt2</i>	I intend to apply resin distillation from <i>D. alatus</i> processing within the next year.	Unlikely – very likely
<i>Adopt3</i>	I intend to produce <i>D. alatus</i> soap using <i>D. alatus</i> processing within the next year.	Unlikely – very likely
Exogenous variables.		

(continued on next page)

Table A1 (continued)

Indicators	Statements	Scale (1–7)
Age	Age of head of household	Year
Cost	The process of substance extraction and relevant <i>D. alatus</i> technology are costly.	Strongly disagree to strongly agree
Experience	Frequency of attending the agricultural training held by government agencies in the past few years.	count
Environmental view	You believe that <i>D. alatus</i> technology provides environmental benefits.	Strongly disagree to strongly agree
Perceived ease of use	The difficulty of <i>D. alatus</i> application is obstructing you from obtaining it.	Strongly disagree to strongly agree

Table A2. Goodness-of-fit indices of the measurement model.

Indices	Satorra & Bentler (SB)	Swain correction (SW)
χ^2	77.030 (df = 30, p = 0.000)	55.210 (df = 30, p = 0.0034)
RMSEA	0.183	0.165
CFI	0.915	0.930
TLI ^a	0.872	0.895
IFI ^a	0.917	0.932
SRMR	0.083	-
CD (R ²)	0.782	-
Swain correction factor (S) = 0.891		

Note: Tucker–Lewis index (TLI) is also known as the non-normed Fit Index (NNFI), Swain correction factor is obtained from STATA 15 software. ^a unaffected by small sample size.

References

- Achavanuntakul, S., Panyakul, W., 2016. Financial Incentives to Encourage Organic Farming in Thailand by Sal Forest - Issuu. Retrieved from. <https://issuu.com/salfores/t/docs/organic-farming-final>.
- Adrian, A.M., Norwood, S.H., Mask, P.L., 2005. Producers' perceptions and attitudes toward precision agriculture technologies. *Comput. Electron. Agric.* 48 (3), 256–271.
- Akihisa, T., Tokuda, H., Ukiya, M., Suzuki, T., Enjo, F., Koike, K., Nikaido, T., Nishino, H., 2004. 3-Epicabraleahydroxylactone and other triterpenoids from camellia oil and their inhibitory effects on Epstein-Barr virus activation. *Chem. Pharm. Bull.* 52 (1), 153–156.
- Akyüz, N.C., Theuvsen, L., 2020. The impact of behavioral drivers on adoption of sustainable agricultural practices: the case of organic farming in Turkey. *Sustainability* 12 (17), 1–20.
- Antonakis, J., 2013. SWAIN: Stata Module to Correct the SEM Chi-Square Overidentification Test in Small Sample Sizes or Complex Models. *Statistical Software Components*, pp. 15–16. Retrieved from. <https://ideas.repec.org/c/boc/bocode/s457617.html>.
- Asanok, L., Kamyto, T., Norsasengri, M., Salinla-um, P., Rodrungruang, K., Karnasuta, N., Navakam, S., Pattanakiat, S., Marod, D., Duengkae, P., Kutintara, U., 2017. Vegetation community and factors that affect the woody species composition of riparian forests growing in an urbanizing landscape along the Chao Phraya River, central Thailand. *Urban For. Urban Green.* 28, 138–149.
- Asfaw, Solomon, Simtowe, Franklin, Shiferaw, Bekele, Haile, Mekbib G., et al., 2011. Agricultural technology adoption, seed access constraints, and commercialization in Ethiopia. *J. Dev. Agric. Econ.* 3 (9), 436–447.
- Attavanich, W., Chantarar, S., Chenphuengpaw, J., Mahasuweerachai, P., Thampanshivong, K., Buthpho, N., 2019. Farms, farmers and farming: a perspective through data and behavioral insights. In: *PIER Discussion Papers*. Puey Ungphakorn Institute for Economic Research.
- Awang, Z., Afthanorhan, A., Asri, M.A.M., 2015. Parametric and non parametric approach in structural equation modeling (SEM): the application of bootstrapping. *Mod. Appl. Sci.* 9 (9), 58–67.
- Bayard, B., Jolly, C., 2007. Environmental behavior structure and socio-economic conditions of hillside farmers: a multiple-group structural equation modeling approach. *Ecol. Econ.* 62 (3–4), 433–440.
- Bentler, P.M., Chou, C.P., 1987. Practical issues in structural modeling. *Socio. Methods Res.* 16 (1), 78–117.
- Beus, C.E., Dunlap, R.E., 1991. Measuring adherence to alternative vs. Conventional agricultural paradigms: a proposed scale. *Rural Sociol.* 56 (3), 432–460.
- Bollen, K.A., Noble, M.D., 2011. Structural equation models and the quantification of behavior. *Proc. Natl. Acad. Sci. U. S. A.* 108 (SUPPL. 3), 15639–15646.
- Boontawee, B., 2001. The Status of In Situ and Ex Situ Conservation of *Dipterocarpus Alatus* Roxb. In Thailand. 171–182. Yogyakarta, Indonesia: ITTO Project PD 16/96 Rev. 4(F).
- Butkhup, L., Samappito, W., Jorjong, S., 2018. Evaluation of bioactivities and phenolic contents of wild edible mushrooms from northeastern Thailand. *Food Sci. Biotech.* 27 (1), 193–202.
- Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q.: Manag. Inf. Syst.* 13 (3), 319–339.
- Dillon, W.R., Bollen, K.A., Long, J.S., 1996. Testing structural equation models. *J. Market. Res.* 33 (3), 374.
- Ervin, C.A., Ervin, D.E., 1982. Factors affecting the use of soil conservation practices: hypotheses, evidence, and policy implications (USA). *Land Econ.* 58 (3), 277–292.
- Fishbein, M., Ajzen, I., 1975. *Belief, Attitude, Intention and Behavior: an Introduction to Theory and Research*. Addison-Wesley, Reading, MA.
- Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. *J. Market. Res.* 18 (1), 39–50.
- Foster, A.D., Rosenzweig, M.R., 2010. Microeconomics of technology adoption. *Annual Rev. Econom.* 2 (1), 395–424.
- Vanclay, Frank, 1992. Barriers to adoption: a general overview of the issues. *Rural Soc.* 2 (2), 10–12.
- Gyau, A., Smoot, K., Kouame, C., Diby, L., Kahia, J., Ofori, D., 2014. Farmer attitudes and intentions towards trees in cocoa (*Theobroma cacao* L.) farms in Côte d'Ivoire. *Agrofor. Syst.* 88 (6), 1035–1045.
- Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2010. *Multivariate Data Analysis*, seventh ed. Pearson Education Ltd, Harlow, Essex, UK.
- Hall, Bronwyn H., Khan, Beethika, 2002. *Adoption of New Technology*. New Economy Handbook.
- Henning, S.A., Zhong, Y., Cardona, H., 2012. Ecological attitudes of farmers and adoption of best management practices. *Southwestern Econom. Proceed.* 31 (2), 57–70.
- Herzog, W., Boomsma, A., 2009. Small-sample robust estimators of noncentrality-based and incremental model fit. *Struct. Equ. Model.* 16 (1), 1–27.
- Hox, J., Bechger, T., 1998. An introduction to structural equation modeling. *Family Sci. Rev.* 11, 354–373. Retrieved from. https://dspace.library.uu.nl/bitstream/handle/1874/23738/hox_98_an+introduction+to+structural+equation.pdf?sequence=1.
- Hu, L.-T., Bentler, P.M., 1995. Evaluating model fit. In: *Structural Equation Modeling: Concepts, Issues, and Applications*. Sage Publications, Inc, Thousand Oaks, CA, US, pp. 76–99.
- Hussain, A., Chauhan, J., Singh, A.K., Yousuf, S., 2009. A study on adoption behaviour of farmers in Kashmir valley. *Indian Res. J. Extens. Educ.* 9 (2), 46–49.
- Jackson, D.L., 2003. Revisiting sample size and number of parameter estimates: some support for the N: q hypothesis. *Struct. Equ. Model.* 10 (1), 128–141.
- Jiang, G., Yuan, K.H., 2017. Four new corrected statistics for SEM with small samples and nonnormally distributed data. *Struct. Equ. Model. Multidiscip. J.* 24 (4), 479–494.
- Jones, R.E., Dunlap, R.E., 1992. The social bases of environmental concern: have they changed over time? *Rural Sociol.* 57 (1), 28–47.
- Jöreskog, K.G., Sörbom, D., Du Toit, S.H.C., 2001. LISREL8: new statistical features. Scientific Software International.
- Jöreskog, K.G., 1970. A general method for estimating linear structural equation system. *ETS Res. Bulletin Series* 1970 (2), i–41.
- Kaewgrajang, T., Sangwanit, U., Iwase, K., Kodama, M., Yamato, M., 2013. Effects of entomycorrhizal fungus *Astraeus odoratus* on *Dipterocarpus alatus* seedlings. *J. Trop. For. Sci.* 25 (2), 200–205.
- Kamyto, T., Asanok, L., 2020. Modeling habitat suitability of *Dipterocarpus alatus* (dipterocarpaceae) using MaxEnt along the Chao Phraya River in Central Thailand. *For. Sci. Technol.* 16 (1), 1–7.
- Kariyasa, K., Dewi, Y.A., 2013. Analysis of factors affecting adoption of integrated crop management farmer field school (ICM-FFS) in swampy areas. *Int. J. Food Agric. Econ.* 1 (2), 29–38.
- Kenny, D.A., 2011, September. SEM: Respecification. Retrieved June 25, 2020, from. <http://davidakenny.net/cm/respec.htm>.
- Kline, R.B., 2015. *Principles and Practice of Structural Equation Modeling*, fourth ed. The Guilford Press.
- Li, Y., Fu, Z.T., Li, H., 2007. Evaluating factors affecting the adoption of mobile commerce in agriculture: an empirical study. *N. Z. J. Agric. Res.* 50 (5), 1213–1218.
- Lui, H., Jamieson, R., 2003. Integrating trust and risk perceptions in business-to-consumer electronic commerce with the technology acceptance model. In: *Conference on*

- Information Systems, (January), 17. Retrieved from. <https://aisel.aisnet.org/ecis2003/60>.
- Marsh, H.W., Balla, J.R., McDonald, R.P., 1988. Goodness-of-fit indexes in confirmatory factor analysis: the effect of sample size. *Psychol. Bull.* 103 (3), 391–410.
- Martínez-García, C.G., Dorward, P., Rehman, T., 2013. Factors influencing adoption of improved grassland management by small-scale dairy farmers in central Mexico and the implications for future research on smallholder adoption in developing countries. *Livest. Sci.* 152 (2–3), 228–238.
- McGinty, M.M., Swisher, M.E., Alavalapati, J., 2008. Agroforestry adoption and maintenance: self-efficacy, attitudes and socio-economic factors. *Agrofor. Syst.* 73 (2), 99–108.
- Mehmetoglu, M., 2015. CONDISC: Stata Module to Perform Convergent and Discriminant Validity Assessment in CFA.
- Meijer, S.S., Catacutan, D., Ajayi, O.C., Sileshi, G.W., Nieuwenhuis, M., 2015. The role of knowledge, attitudes and perceptions in the uptake of agricultural and agroforestry innovations among smallholder farmers in sub-Saharan Africa. *Int. J. Agric. Sustain.* 13 (1), 40–54.
- Muzari, W., Gatsi, W., Muvhunzi, S., 2012. The impacts of technology adoption on smallholder agricultural productivity in sub-saharan africa: a review. *J. Sustain. Dev.* 5 (8).
- Mwangi, M., Kariuki, S., 2015. Factors determining adoption of new agricultural technology by smallholder farmers in developing countries. *ISSN* 6 (5), 2222, 1700. Retrieved from. www.iiste.org.
- Mwase, W., Sefasi, A., Njoloma, J., Nyoka, B.I., Manduwa, D., Nyaika, J., 2015. Factors affecting adoption of agroforestry and evergreen agriculture in southern africa. *Environ. Nat. Resour. Res.* 5 (2).
- Pierpaoli, E., Carli, G., Pignatti, E., Canavari, M., 2013. Drivers of precision agriculture technologies adoption: a literature review. *Procedia Technology* 8, 61–69.
- Podsakoff, N.P., Shen, W., Podsakoff, P.M., 2006. The role of formative measurement models in strategic management research: review, critique, and implications for future research. *Res. Methodol. Strat. Manag.* 3, 197–252.
- Prager, K., 2011. Socio-economic Factors Influencing Farmers' Adoption of Soil Conservation Practices in Europe CONTRACTS2.0-Co-Design of Novel Contract Models for Innovative Agri-Environmental-Climate Measures and for Valorisation of Environmental Public Goods View Projec. Retrieved from. <https://www.researchgate.net/publication/284885301>.
- Rehman, T., 2000. Using social-psychology models to understand farmers' conservation behaviour. *J. Rural Stud.* 16 (1), 117–127.
- Rennenberg, N., 2002. Assessment of Land Use Changes in Mukdaham and Nakhon Phanom Provinces (NE Thailand) by Means of Remote Sensing. Retrieved from. [http://books.google.com/books?hl=en&lr=&id=84TqDAAAQBAJ&oi=fnd&pg=PA4&dq=Rennenberg,+Nils+\(2002\).+Assessment+of+land+use+changes+in+Mukdaham+and+Nakhon+Phanom++provinces+\(NE+Thailand\).+Diplom.de.+&ots=tpoVii1qLi&sig=08xcelIxx29hg2IIHo3Y1biQgew](http://books.google.com/books?hl=en&lr=&id=84TqDAAAQBAJ&oi=fnd&pg=PA4&dq=Rennenberg,+Nils+(2002).+Assessment+of+land+use+changes+in+Mukdaham+and+Nakhon+Phanom++provinces+(NE+Thailand).+Diplom.de.+&ots=tpoVii1qLi&sig=08xcelIxx29hg2IIHo3Y1biQgew).
- Rezaei-Moghaddam, K., Salehi, S., 2010. Agricultural specialists' intention toward precision agriculture technologies: integrating innovation characteristics to technology acceptance model. *Afr. J. Agric. Res.* 5 (11), 1191–1199.
- Rogers, E.M., 1983. Diffusion of Innovations, third ed.
- Satorra, A., Bentler, P.M., 1994. Corrections to test statistics and standard errors in covariance structure analysis. In: von Eye, A., Clogg, C.C. (Eds.), *Latent variables analysis: application for developmental research*. Sage Publications, Inc., pp. 399–419.
- Schaak, H., Mußhoff, O., 2018. Understanding the adoption of grazing practices in German dairy farming. *Agric. Syst.* 165, 230–239.
- Suiyui, C., Sudajan, S., Katekaew, S., Senawong, K., Laloon, K., 2019. Production of gasoline-like-fuel and diesel-like-fuel from hard-resin of Yang (*Dipterocarpus alatus*) using a fast pyrolysis process. *Energy* 187, 115967.
- Swain, A.J., 1975. Analysis of Parametric Structures for Variance Matrices. Adelaide.
- Szajna, B., 1996. Empirical evaluation of the revised technology acceptance model. *Manag. Sci.* 42 (1), 85–92.
- Tang, J., Folmer, H., Xue, J., 2013. Estimation of awareness and perception of water scarcity among farmers in the Guanzhong Plain, China, by means of a structural equation model. *J. Environ. Manag.* 126, 55–62.
- Thangata, P.H., Alavalapati, J.R.R., 2003. Agroforestry adoption in southern Malawi: the case of mixed intercropping of *Gliricidia sepium* and maize. *Agric. Syst.* 78 (1), 57–71.
- Thompson, A.W., Reimer, A., Prokopy, L.S., 2015. Farmers' views of the environment: the influence of competing attitude frames on landscape conservation efforts. *Agric. Hum. Val.* 32 (3), 385–399.
- Uematsu, H., Mishra, A.K., 2010. Can education Be a barrier to technology Adoption ?. In: *Agricultural & Applied Economics Association 2010 AAEA*, p. 38.
- Verma, P., Sinha, N., 2017. Role of attitude as mediator of the perceived ease of use and behavioural intention relationship. *Int. J. Manag. Concepts Philos.* 10 (3), 227.
- Verma, P., Sinha, N., 2018. Integrating perceived economic wellbeing to technology acceptance model: the case of mobile based agricultural extension service. *Technol. Forecast. Soc. Change* 126, 207–216.
- Weston, R., Gore, P.A., 2006. A Brief Guide to Structural Equation Modeling.
- Wheeler, S.A., 2008. What influences agricultural professionals' views towards organic agriculture? *Ecol. Econ.* 65 (1), 145–154.
- Willock, J., Deary, L.J., Edwards-Jones, G., Gibson, G.J., McGregor, M.J., Sutherland, A., Dent, B., Morgan, O., Grieve, R., 1999. The role of attitudes and objectives in farmer decision making: business and environmentally-oriented behaviour in Scotland. *J. Agric. Econ.* 50 (2), 286–303.
- Wu, J.H., Wang, S.C., 2005. What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Inf. Manag.* 42 (5), 719–729.
- Yazdanpanah, M., Hayati, D., Hochrainer-Stigler, S., Zamani, G.H., 2014. Understanding farmers' intention and behavior regarding water conservation in the Middle-East and North Africa: a case study in Iran. *J. Environ. Manag.* 135, 63–72.
- Yongram, C., Sunghong, B., Puthongking, P., Weerapreeyakul, N., 2019. Chemical composition, antioxidant and cytotoxicity activities of leaves, bark, twigs and oleoresin of *dipterocarpus alatus*. *Molecules* 24 (17), 3083.
- Zeweld, W., Van Huylbroeck, G., Tesfay, G., Speelman, S., 2017. Smallholder farmers' behavioural intentions towards sustainable agricultural practices. *J. Environ. Manag.* 187, 71–81.