Behavioral Interest Identification for Farm Mechanization Development using Path Analysis and Neuro-fuzzy Models

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ABSTRACT

This paper studies the behavioral side of people's interest regarding farm mechanization development. The objectives were to identify and explain the predictor and the most important variables of perceptional and behavioral characteristics of young people to the interest in farming jobs and farm machines in a region. Path analysis and neuro-fuzzy models were developed to take advantage of both techniques to explain the causal reasoning, nonlinear representation, and the human-likeness reasoning of the imprecise behavioral and perceptional data. The data used for this research were students observed from three upper secondary schools in North Sulawesi Province, Indonesia, using questionnaires we designed. The path analysis model identifies that the gender variable is the direct positive predictor variable of the interest in farming jobs. The interest in farming jobs, the willingness to take jobs related to farming and the gender variables are the predictor variables of the interest in hand tractors. The neuro-fuzzy approach identifies that the perception of risk and the ease perception of the load of overall farming activities are the important variables for the interest in farming jobs, whereas the interest in farming jobs and the ease perception of the load of overall farming activities are the most important prediction variables for the interest in hand tractors. The models and information gathered support a behavioral consideration for incorporating it with the technical and economical farm machine selection system in such a region.

Keywords: Behavioral interest identification, farming jobs, farm mechanization, neuro-fuzzy, path analysis.

1. INTRODUCTION

The issue of fewer young people who are interested in farming jobs in agro-developing countries raises a problem in the region, whereas the unemployment is increasing and the available arable land is not farmed optimally. Working in the open field under uncertain weather, low payoff, risk factors, undeveloped policy, and the drudgery of work are some factors that are estimated to be the causes of the problem. Such things influence most farmers to have a negative perception of farming so that if it is possible, the career priority for their educated children is in non-farming (Mundlak *et al.*, 2002).

Farm mechanization has affected the increment of the yield production. It also accounts to alleviate the drudgery of manual tillage, which may be important to keeping younger people interested in farming (So *et al.*, 2001). The authority needs to develop a policy based on technical, economic, socio-economic, gender, rural client acceptability, and environmental criteria (Gass *et al.*, 1997). A behavioral approach is also actually relevant to consider in developing an appropriate mechanization for a traditional or a transitional state of traditional to modern farming system.

The problem of an appropriate mechanization is an extremely wide-ranging one, which requires in-depth technical analysis and a holistic approach. To solve this problem, mechanization needs to be considered not just in technical terms but also as a component in a system where development relies upon establishing a series of essential "collateral" activities within the various countries (Pawlak *et al.,* 2002). Furthermore, in such a production system one has to look at the production system as a human-centered process that involves sequential sensing, decision making and execution of actions (Cros *et al.*, 2003). Misapplied mechanization inputs can be found in many technical co-operation projects in an uncoordinated way and an unfortunate fact reports that only a very few mechanization projects aimed at "transferring" technology to developing countries can claim to have been completely successful (Clarke, 2000). The consequence of failing to apply the holistic approach in a local system would have an insignificant positive impact on crop production income and household labor economy (Panin, 1994).

The study of the behavioral side such as young people's interest in farming jobs and farm machines in developing countries is rarely considered in farm policy development of farm mechanization in comparison to the abundance of information on the economic and technical side. As farming activities such as in horticulture can make old people living in convenience in an optimum controlled environment (Hayashi *et al.*, 2003) and because of the issue of fewer young people being interested in farming jobs, it is also interesting to get information about the convenient perception of young people regarding the farming activities. The information gathered may support an evaluation for planning a most desired and suitable system in a farm region; the prior is a behavioral consideration, and the latter is a combination of behavioral, technical, and socio-economic considerations.

Problems may arise in behavioral study, such as in gathering a real data, which is timely and costly and deals with the complex behavior of the people observed, and in analyzing and simulating the complex data. It deals with the inherent complexity of behavioral characteristics and perception in regard to imprecise data and uncertainties, which are subjective and qualitative rather than quantitative. A proper system to analyze and simulate such kind of data is a need.

Linear system models are commonly used, such as path analysis in social and psychological studies, to determine the effect of each variable modeled as shown in arrows and to find which variable affects it directly and indirectly (Wahana, 2005). Path analysis is a method to examine direct and indirect relationships of variables modeled. It uses a path diagram to represent the proposed antecedents and consequences among the variables in the model (Susskin *et al.*, 2000). Path analysis has been satisfactorily explaining the predictor variables for passengers' behavioral intentions in airline service quality according to their perceptions to some airlines service (Park *et al.*, 2004). It confirms a significant relationship that education and training of project managers is important in influencing the time delivery of construction projects in the relationship of a human capital and a project time performance (Brown, 2006). The path analysis also can test a model of the impact of students' perceptions of classroom structures on their self-efficacy, perceptions of the instrumentality of class work, and their achievement goals in a particular classroom setting (Greene *et al.*, 2004). Furthermore, it explains well the factors underlying the selection of organic food among Australian consumers according to their attitudes and perceptions (Lockie *et al.*, 2004).

In order to handle imprecise information and to reason under vagueness and uncertainty, fuzzy logic has superiority. Its human-likeness can provide human-like descriptions of knowledge and imitate a ‘‘human’’ mind and decision (Drigas, *et al.,* 2004). It can modify the input parameters to the output optimization that has been applied to a wide variety such as in biological, management, and decision support (Rao and Rao, 1996). The combination of Artificial Neural Networks (ANN) and fuzzy sets offers a powerful method to model the behavioral characteristics, as ANN is strong in learning and adaptation of patterns and fuzzy set theory is strong in imprecise reasoning (George & Cardullo, 2001). The hybrid of ANN and fuzzy or neuro-fuzzy technique incorporates the strengths of both.

This paper proposes behavioral interest identification using path analysis and neuro-fuzzy models to study young people’s interest in farming jobs and farm machines for consideration in farm mechanization development. The path analysis is used to perform the causal reasoning, and the neuro-fuzzy models are used for learning the nonlinear data and constructing a human likeness of human behavior reasoning on farm mechanization development. The objectives of the models were to identify and explain the predictor variables of young people’s interest in farming jobs and farm machines using developed path analysis model and to identify and select the best predictor variables by testing and analyzing the best selected variables on young people’s interest in farming jobs and farm machines using neuro-fuzzy models.

2. PERCEPTION, INTEREST, AND BEHAVIORAL DECISION

2.1 Behaviorism and Decision

The behavioral approach came to be known as the A → B → C model of behavior (Skinner, 1953). Antecedent conditions (A) are things a person can see, hear, feel, and remember. Behaviors (B) are the actions that a person exhibits in the presence of A. Consequences (C) are the outcomes of the person’s actions or behavior. Behaviors leading to desirable outcomes are positively reinforced and become habits.

Behavioral decision explores the actual decisions that people make as individuals, groups, and organizations (Mellers, 2001). It studies what the people actually do. The other is normative decision, which studies what the people should do (Molz, 2005). This field has provided psychological insights about utilities and beliefs and has offered descriptive accounts of choice. Behavioral approaches in agricultural studies seek to understand the behavior of individual decision makers, focusing on psychological constructs such as attitudes, values, and goals but also relevant data such as economic and succession status, and they employ largely quantitative methodologies, such as Likert-type scaling, for investigating psychological constructs (Burton, 2004).

It is necessary to gather relevant information to make appropriate conclusions about what is likely to happen. The error happens when there is a psychological barrier, which leads to systematic errors estimating the likelihood of uncertain events; mistakes in manipulating probabilities; misinterpretation of the meaning of probabilistic relationships; mistakes in identifying and assessing values underlying decisions; and failure to combine information about probabilities and values in a coherent way. Any or all of these biases can threaten good decision making (Maguire & Albright, 2005).

2.2 Perception, Interest, and Decision

Perception is a component of mind on which the decision is identified. In farming it is affected by the uncertainty of variable states such as risk of weather, load of works, and the return endeavor of farming jobs outcome. Interest is a product of deployment of attention from desire to wonder in the human mind, aroused and depressed by autocatalysis, sensory input, and the state of the rest of mind (Lesser & Murray, 1998). Interest is a function of attention, perception, and some states in memory, where the attention is influenced by the human behavior and emotion. The Eq.(1) and (2) represent some states that influence the interest in mind, which is shown in Figure 1.

$$N_t = f(b_t + e_t) \tag{1}$$

$$I_t = f(N_t + p_t + m_t) \tag{2}$$

Where N is attention, I is interest, p is perception of object, e is emotion, b is behavioral characteristics, m is some other states in memory, and the subscript t is time dependent. The arousal or the decay of attention to an object, which increases or decreases the interest, explains the mechanism of behavioral interest as shown in Figure 1. It means that the more attention given to an object, the more interest the people have in the object, which implies that it would be more possible to take, choose, or use the most desired object. It may be stated that the probability of the object intending to choose (P_t) is a function of interest in the object (I_t), as represented in the Eq. (3).

$$P_t = f(I_t) \tag{3}$$

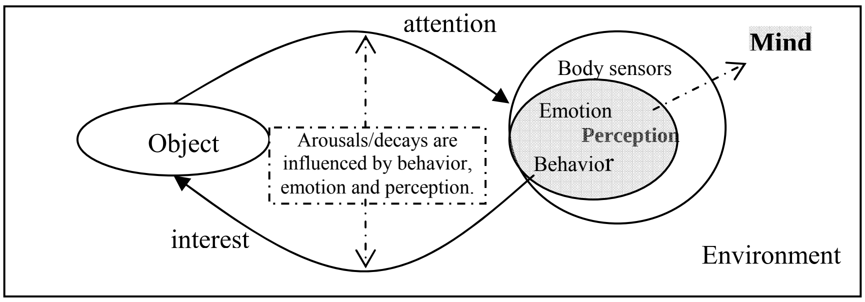


Figure 1. The arousals and decays of attention and interest in an object.

The long-term fluctuation is the most behavior-dependent; otherwise, it is emotion-dependent. Both of them affect the variation of human decision, which is individually different and dynamic (Tooy & Murase, 2006). People's perception and behavior affect the way people make decisions through the arousal and the decay of attention and interest in an object, in which the ability to identify what kind of perception and behavioral characteristics of the interest predictors of an object would help to know the interested object according to the preference. A new or strange object such as a new farm machine generally draws attention faster for the first time than the object that people had already known. But as time goes on, the more risk gained, the more careful the people are to take interest in the object. The prior bad experience with a kind of machine creates resistance in the memory, which then decays interest in the machine in the future or causes rejection.

Behavioral observation study gives more understanding of the behavior and perception that produce attention and other desired objects, which are called preferences. It studies the behavior that allows the person to avoid or escape other undesired activities to make security from risk because of its sensory consequences such as pain relief and feeling well (Starin, 1999).

3. MATERIALS AND METHODS

3.1 Data, Instruments, and Method

The questionnaire was designed to obtain perception and behavioral characteristics, and as this research was not collecting continuous data in a timely manner, Eq. (1) and (2) were simplified to Eq. (4) as the behavioral interest model for empirical study.

$$I = f(p,b) \tag{4}$$

Where I is interest, f is function, p is perception, and b is behavioral characteristics. The farming activity considered was maize farming, which has been intensifying and extending in the region, where more than 30% of the labor force worked in farming. The farm machine considered was the hand tractor. It is already known and estimated to be suitable to the small-scale farm characteristics in the region, but it was still rarely used in the region.

Table 1. Code, type, and description attributes of questionnaires

Code	*Type*	*Behavioral characteristics and Perceptional Attributes*
B1	Binary	Gender
B2	Binary	Parent is farmer
B3	Binary	Future job choice related to farming
F	Categorical	Force labor where the student lives
M1	Multistage	The ease of financial capital
M2	Multistage	The ease of soil tillage
M3	Multistage	The availability of fertilizer
M4	Multistage	The availability of seed
M5	Multistage	The ease of irrigation management
M6	Multistage	The ease of maize drying
M7	Multistage	Transportation to market perception
M8	Multistage	The ease of selling the yield
M9	Multistage	The ease of farming jobs
M10	Multistage	Pest risk perception
M11	Multistage	Natural risk disaster perception
M12	Multistage	Social risk perception of farming jobs
M13	Multistage	Farm economic outcome perception
M14	Multistage	The interest in farming jobs
M15	Multistage	The interest in hand tractors

The code, type, and attributes of the questionnaires are shown in Table 1. Binary type was yes or no (1 or 0). The multistage type was Likert scale, from one to seven, which meant from the lowest agree to the highest agree or the worst to the best. The value of F was determined according to the subjective categorization. It was 0.2 at IH<=25%, then 0.5 at 25%>IH>50%, and 0.8 at IH>=50%, where IH was the percentage of the inhabitants working in the farming sector in the village or place where the student lived. It was observed as a social environment independent variable hypothesized as influencing the positive student interest in farming jobs. The data variables of *M1, M2, M3, M4, M5, M6, M7, M8,* and *M9* were united as *M1_M9,* representing the ease perception of the load of overall farming activities. The data variables of *M10, M11, and M12* were united as *M10_M12,* representing the perception for the risk of farming jobs.

The data were observed and collected from the third grade of three upper secondary schools in North Sulawesi Province, Indonesia, in April-May 2006. The choice of the third grade was based on the fact that after graduation most students were willing to take a job, otherwise continuing study at the higher school in the region. The questionnaires with some pictures of hand tractor were given to the students for about 15 minutes to answer after some introduction. The answers represented the perception and behavior responses of self perception regarding the interest in farming jobs and hand tractors. Data from 74 students were selected after cleaning the incomplete data. From two general secondary schools there were 60 respondents, and from an agricultural secondary school there were 14 respondents. The path analysis model and the statistics' preprocessing data were implemented on Lisrel and SPSS, and the neuro-fuzzy model was implemented on Matlab with fuzzy toolbox. The flowchart of this study and the prospect to be a part of a behavioral decision support system (DSS) on farm machine selection is shown in Figure 2.

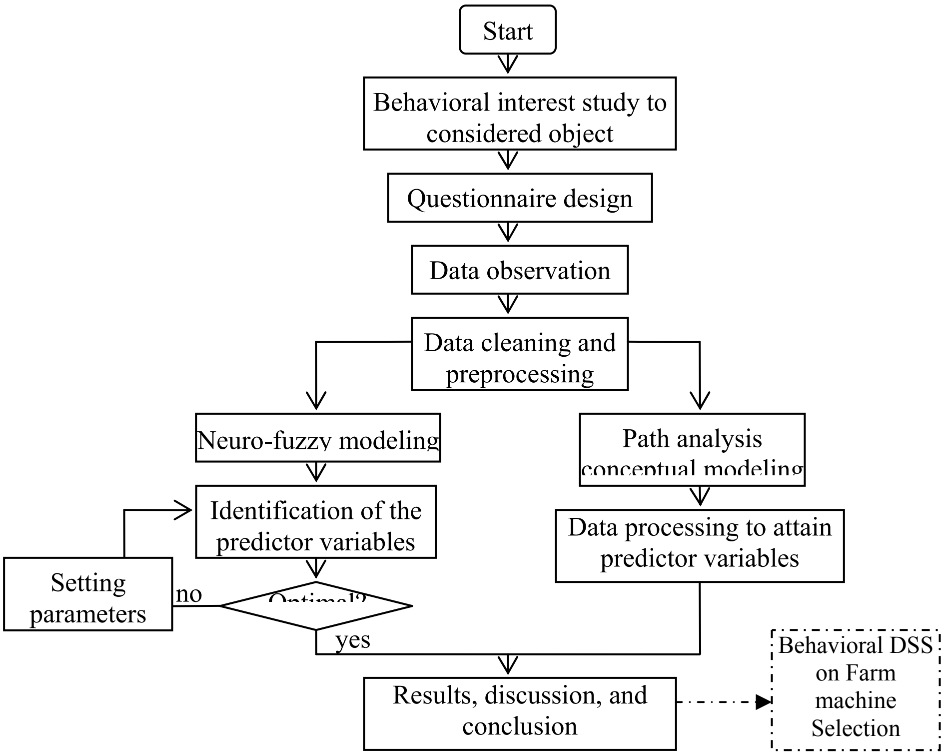


Figure 2. The flowchart of study as a part of behavioral DSS on farm machine selection

3.2 Path Analysis Conceptual Model Development

A path analysis was used for quantitative interpretations of potential causal relationships. A path diagram represents the proposed antecedents and consequences among the variables in the model. Arrows are used to symbolize the hypothesized relationships and the direction of the influence in the model. In the path model, a distinction is drawn between exogenous variables (independent variables) and endogenous variables (dependant variables). Exogenous variables' influence is outside the model, and endogenous variables have influence within the model. The key variables considered in modeling interest in farming jobs and hand tractors include gender, parent's background, future job related to farming, perception of some activities and the load of overall farming jobs, the risk perception, social perception, and economic outcome (Table 1).

The conceptual model (fig. 3) was modeled to identify the possible relationship of each variable to the behavioral interest in hand tractor. The conceptual model states some hypotheses to be tested empirically as below:

- *B1* (gender) has a *positive* impact on *B3* (future job choice related to farm), *M13* (farm economical outcome perception), *M14* (the interest in farming jobs) directly, and *M15* (the interest in hand tractors) indirectly.
- *B2* variable (parent is a farmer) has a *positive* impact on *B3* (future job choice related to farming) and *M14* (the interest in farming jobs) directly and on *M15* (the interest in hand tractors) indirectly.
- *B3* (future job choice related to farm) has a positive impact on *M14* (the interest in farming jobs) and *M15* (the interest in hand tractors) directly.
- *F* (percentage of farmers where the student lives) has a positive impact on B3 (future job choice related to farming) and *M14* (the interest in farming jobs) directly and on *M15* (the interest in hand tractors) indirectly,
- *M1-M9* (ease perception of the load of overall farming activities) has a positive impact on *B3* (future job choice related to farming) and *M14* (the interest in farming jobs) directly and on *M15* (the interest in hand tractors) indirectly.

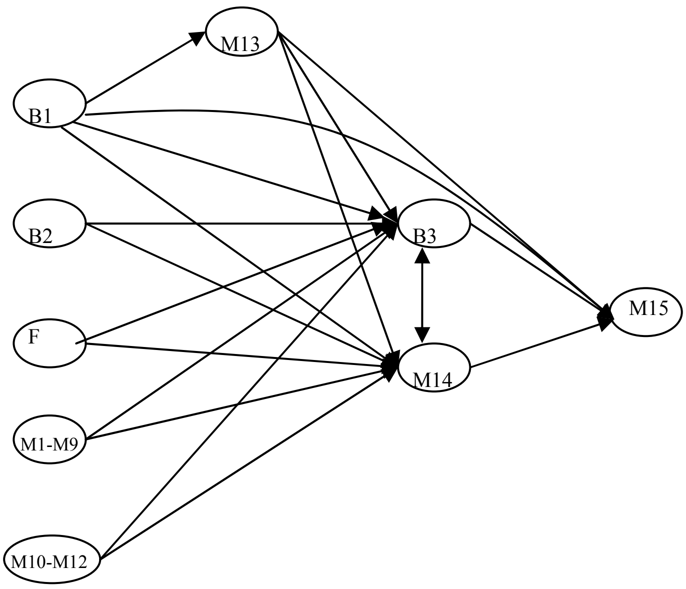


Figure 3. Conceptual model of path analysis structure.

- *M10-M12* (risk perceptions) have a *negative* impact on *B3* (future job choice related to farming) and *M14* (the interest in farming jobs) directly and on *M15* (the interest in hand tractors) indirectly.

- *M13* (farm economical outcome perception) has a *positive* impact on *B3* (future job choice related to farming), *M14* (the interest in farming jobs), and *M15* (the interest in hand tractors) directly.
- *M14* (the interest in farming jobs) has a *positive* impact on *B3* (future job choice related to farming) and *M15* (the interest in hand tractors) directly.

The model is structured and specified by the following path equations:

$$M13 = b_{11}*B1 + e_1 \tag{5}$$

$$M14 = b_{21}*B1 + b_{22}*B2 + b_{23}*F + b_{24}*M1\_M9 + b_{25}*M10\_M12 + e_2 \tag{6}$$

$$B3 = b_{31}*M14 + b_{32}*B1 + b_{33}*B2 + b_{34}*F + b_{35}*M1\_M + b_{36}*M10\_M12 + e_3 \tag{7}$$

$$M15 = b_{41}*M13 + b_{42}*M14 + b_{43}*B3 + b_{44}*B1 + e_4 \tag{8}$$

Where the *e's* are the error variables that reflect unexplained variance (the effect of unmeasured variables) plus measurement error. The *b's* are the path coefficients (β) of each exogenous variable on its priors and the partial weights controlling for other priors for the given dependent variable. The subscripts of the *b's* are the equation number and variable number. The significant path coefficient of a variable can be identified if the value of t calculation (t_{cal}) is bigger than the value of t table (t_{tab}).

The path coefficients were used to decompose correlations into direct and the indirect effects to the interest in hand tractor variable. The account of each independent variable to the dependent variable was obtained by multiplying the path coefficients with the zero order Pearson correlation coefficients. The total effect that accounts to the endogenous variable was the total coefficient of direct effect and indirect effect of the independent variables.

3.3 Neuro-Fuzzy Model Development

There were two proposed behavioral interest identification models as a nonlinear regression type using data variables in Table 1. The first model used *B1, B2, B3, F, M1_M9, M10_M12,* and *M13* as the input to the interest in farming jobs, and the second model used *B1, B2, B3, F, M1_M9, M10_M12, M13, and M14* as the input to the hand tractor interest prediction. The adaptive neuro-fuzzy inference system (ANFIS) technique was used for data evaluation and selecting the best selected predictors of each model. The models built some fuzzy models of input, such as one input, two inputs, and three inputs, to train ANFIS using the least-squares method.

The 74 data observed were divided into training and test data sets for 37 of each randomly. The training set was used to tune the fuzzy model, while the testing set was used to determine when training should be terminated to prevent over fitting. The selection of the best predictors after some epochs was the lowest training root mean square error (RMSE) as the error consideration. The ANFIS training was extended for prediction until the test error was minimal to test the ability to predict the target as the best selected predictor variable.

The inference methods used in the fuzzy implication process were: and method was prod, or method was max, and the defuzzification method was weight average. Most of the data were ordinal, where the others were binary, thus the number of modified parameters used was limited to two. The number of rules for the two models was four, and each weight of rules was one.

The ANFIS used a five-layer feed-forward network to search for fuzzy decision rules. The scheme of ANFIS is shown in Figure 4. A fuzzy inference system was created using the input-output data set, and the membership function parameters were adjusted using back propagation algorithm with a least squares method (Jang, 1993).

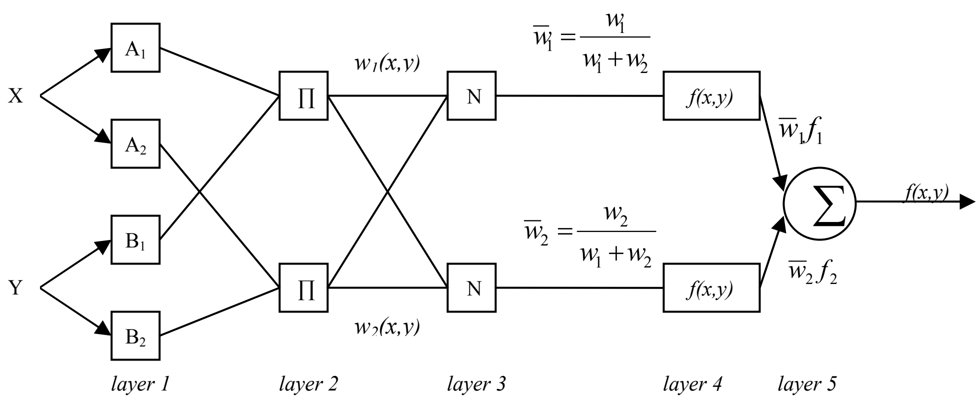


Figure 4. Adaptive neuro-fuzzy inference system scheme.

Considering two inputs x and y and one output, the rule base contained Sugeno-type fuzzy if-then rules and models as summarized as follows:

Rule 1: IF x is A_1 and y is B_1 THEN $f_1 = p_1x + q_1y + r_1$
Rule 2: IF x is A_2 and y is B_2 THEN $f_2 = p_2x + q_2y + r_2$

Where x and y are the inputs to the node i; Ai and Bi are the linguistic labels (low, medium, high) characterized by membership functions and p_i, q_i, and r_i are the consequence parameters (i=1 or 2).

Layer 1: each node generates membership grades of the inputs that belong to each of the appropriate fuzzy sets by using the membership functions. A node output O_i^1 is defined by:

$$O_i^1 = \mu \mathrm{A}_i(x) \quad \text{for } i = 1,2; \quad O_i^1 = \mu \mathrm{B}_{i-2}(y) \quad \text{for i} = 3, 4 \tag{9}$$

where μA_i and $\mu \mathrm{B}_i$ are the appropriate membership functions for A_i and B_i fuzzy sets. Bell-shaped membership function was used to determine the membership grades:

$$O_i^1 = \mu A_i(x) = \frac{1}{1 + ((x - c_i)/a_i)^{2bi}} \tag{10}$$

Where $\{a_i, b_i, c_i\}$ is the membership function parameter set that changes the shape of membership function from 1 to 0. These parameters are referred to as premise parameters. *Layer 2*: in this layer every node is a fixed node labeled Π to get one output representing the results of the antecedent for a fuzzy rule that is firing strength. The outputs of firing strength O_i^2 are the products of the corresponding degrees obtaining from layer 1, as below:

$$O_i^2 = w_i = \mu A_i(x)\mu B_i(y), \quad i = 1,2 \tag{11}$$

Layer 3: in this layer the main target is to compute the ratio of firing strength of each i^{th} rule to the sum of all rules' firing strength. The firing strength in this layer is normalized as $\overline{w}_i$:

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_i wi}, \; i = 1,2 \tag{12}$$

Layer 4: in this layer the contribution of i^{th} rule towards the total output or the model output and/or the function defined below is calculated:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i), i = 1,2 \tag{13}$$

Where $\overline{w}_i$ is the i^{th} node's output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set, which in this layer will be referred to as consequence parameters and also the coefficients of linear combination in the Sugeno inference system.

Layer 5: the single node in this layer computes the overall output as the summation of all incoming signals. Each rule's fuzzy results are transformed into output in this layer by defuzzification process.

$$f(x,y) = \frac{w_i\,(x,y) f_1(x,y) + w_2(x,y) f2(x,y)}{w_1(x,y) + w_2(x,y)} = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{14}$$

$$Q_i^5 = f(x,y) = \sum_i \overline{w}_i f_i = \overline{w}_i f_1 + \overline{w}_i f_2 = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{15}$$

ANFIS applies the hybrid learning algorithm. The gradient descent method was used to assign the nonlinear input parameters (a_i, b_i, c_i), and identification of the linear output parameters (p_i, q_i, r_i) used the least-squares method (Jang *et al.*, 1997). Consequently, the hybrid-learning algorithm was used for an effective search of the optimal parameters of the ANFIS, and the consequent parameters were identified by the least squares method.

4. RESULTS AND DISCUSSIONS

The descriptive statistics as a result of preprocessing data are shown in Table 2. The ratio of skewness represents the normal distribution for values smaller than two and greater than negative two.

Table 2. Descriptive statistics of data variables

Variable	Mean	Standard	Skewness	Std.error of	Skewness
B1	0.459	0.5	0.166	0.279	0.59
B2	0.5	0.5	0	0.279	0.00
B3	0.23	0.42	1.312	0.279	4.70
F	0.659	0.218	-1.253	0.279	-4.49
M1	4.405	1.23	-0.279	0.279	-1.00
M2	5.068	1.32	-0.497	0.279	-1.78
M3	4.405	1.51	-0.208	0.279	-0.75
M4	4.946	1.37	-0.291	0.279	-1.04
M5	4.892	1.42	-0.365	0.279	-1.31
M6	4.662	1.33	-0.252	0.279	-0.90
M7	5.068	1.32	-0.571	0.279	-2.05
M8	4.581	1.25	-0.103	0.279	-0.37
M9	4.054	1.27	0.061	0.279	0.22
M10	4.257	1.51	-0.181	0.279	-0.65
M11	3.784	1.65	0.055	0.279	0.20
M12	4.203	1.17	-0.091	0.279	-0.33
M13	5.554	1.15	-0.61	0.279	-2.19
M14	4.392	1.69	-0.538	0.279	-1.93
M15	4.743	1.95	-0.435	0.279	-1.56

The Table 2 shows that *B3* (future job choice related to farming)*, F (*force labor in village work in farming*), M7* (the risk perception of natural disaster), and *M13* (farming outcome) are not in normal distribution. As the Likert scale from one to seven is from the lowest to the highest (multistage) and 0 and 1 (binary), the "Mean" in Table 2 explains that the most respondents do not want to work in farming in the future (*B3*), live in the village where most of the force labor works in farming (*F*), perceive that the risk of natural disaster is low (*M7*), and perceive that the farming outcome in the region is promising (*M13*).

4.1 The Path Analysis Model

The path coefficients (the β's) for the proposed model among the variables are depicted in Figure 5. The path coefficients explain the relationships value of the independent variables to the dependant variables (*M13, M14, B3, and M15*) in the conceptual model as hypothesized. Structural equations of path analysis results are shown in Eqs. (16), (17), (18), and (19).

$$M13 = 0.14*B1 + e_1 \qquad (16)$$

t_{cal} are 1.00 and 5.83 respectively, e_1 is 0.87, and $R^2 = 0.014$.

$$M14 = 0.40*B1 + 0.21*B2 - 0.12*F + 0.083*M1\_M9 - 0.19*M10\_M12 + e_2 \qquad (17)$$

t_{cal} are 2.52, 1.40, -0.82, 0.63,-1.41, and 5.83 respectively, e_2 is 0.84, and $R^2 = 0.11$.

$$B3 = 0.024*M14 - 0.21*B1 + 0.044*B2 - 0.079*F + 0.0092*M1\_M9 - 0.038*M10\_M12 + e_3 \qquad (18)$$

t_{cal} are 0.26, -1.63, 0.38, -0.68, 0.091, -0.36, and 5.83 respectively, e_3 is 0.49, and $R^2 = 0.067$.

$$M15 = 0.025*M13 + 0.44*M14 + 0.30*B3 + 0.24*B1 + e_4 \qquad (19)$$

t_{cal} are 0.25, 4.42, 2.25, 1.91, and 5.83 respectively, $e_4 = 0.61$, and $R^2 = 0.32$.

The equations show that some variables have positive impacts on and significant relationships to the interest in hand tractors (*M15*) as hypothesized, but some variables have negative and insignificant relationships. The significant relationship is if the value of $t_{cal} > t_{tab,}$ and it explains which variables are the predictor variables and which variables are not the predictor variables for the hypothesized model.

The interest in farming jobs (*M14*) has positive impacts on and significant relationships to the interest in hand tractors (*M15)* (β=0.44, and $t_{cal} = 4.42 > t_{tab} = 1.96$ at α=5%). In other words, greater student interest in farming jobs implies greater students interest in hand tractors. It can be reasoned that the educated young people have already known of the hand tractor's usefulness to farming jobs, as they have been taught in school. Thus, as they are interested in farming jobs, it influences the positive perception of the hand tractor in the farming jobs.

The future job choice related to farm variable (*B3)* has positive impacts on and significant relationships to the greater interest in hand tractors (*M15*) ($\beta = 0.30$, and $t_{cal} = 2.25 > t_{tab} = 1.96$ at α = 5%). It implies that the student who has interest in working in the area of farming in the future considers the hand tractor to support his or her job. However, data shows just a few students interested in working in farming in the future (Table 2). More inspection of the observed data shows that the most interested students, who have future job related to farming, are from an agricultural secondary school. This implies that the students' knowledge of the hand tractor function and the past interest or choice to study in an agricultural secondary school are related to the positive influence on the future job choice related to farming.

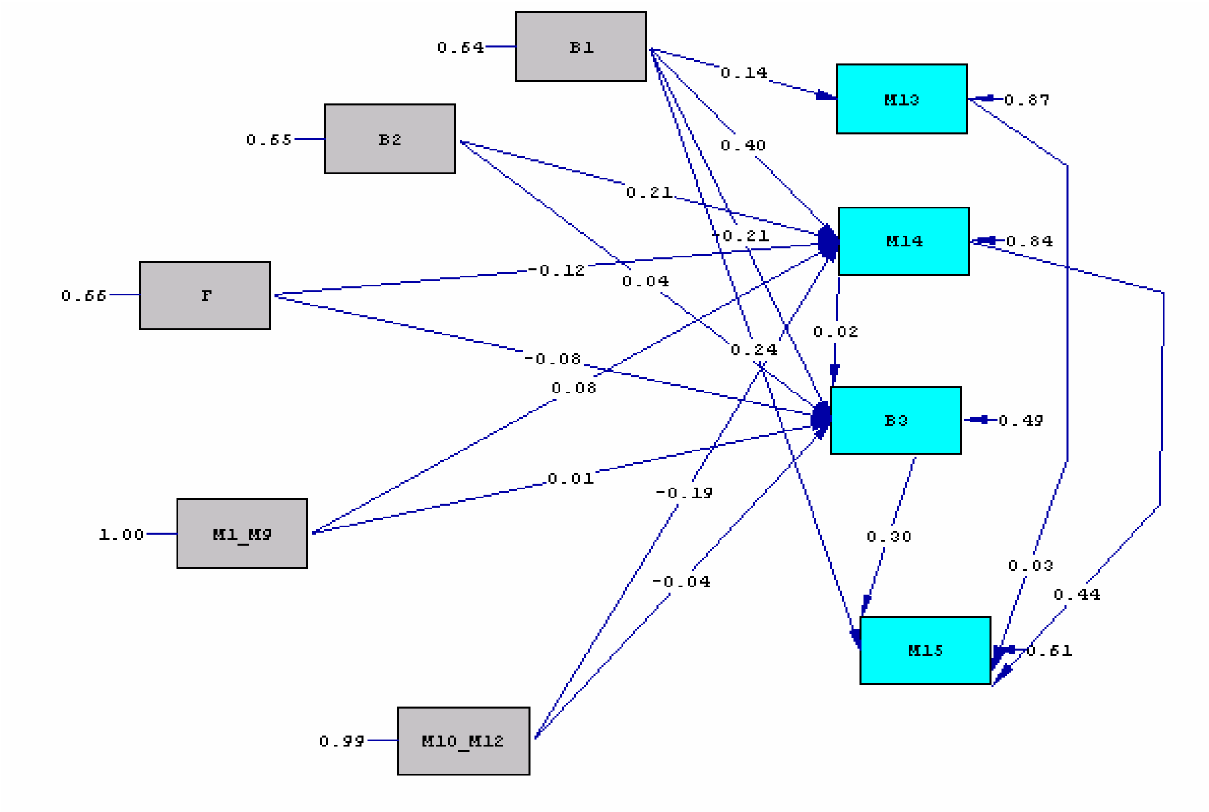


Figure 5. Path model with path coefficients for predictions of interest to hand tractors.

In the direct relationship, the gender variable (*B1*) has positive impacts on and significant relationships to the interest in hand tractors (*M15*) (β=0.24, and t_{cal} =1.91> t_{tab}=1.68 at α =10%). The data inspection shows that it is the males who want to use hand tractors more than the females. The significant value shows that the interest in hand tractors can be predicted by the gender variable that is explained by the bigger number of male students' interest in hand tractor compared to the female students'. It has such a meaning that farming jobs in the regions are still perceived as being male activities not female.

In the case of the interest in farming jobs (*M14*) as the dependant variable, the gender variable (*B1)* as the independent variable has a positive impact and significance (β= 0.40, and t_{cal}=2.25> t_{tab}=1.96 at α =5%). The data inspection shows that in *B1* variable (Table 2), the male students were more interested in farming jobs (*M14*) than the female students were. The hypothesized model of the gender variable (*B1*) to the interest in farming jobs (*M14*) is a direct relationship, and as the interest in farming jobs (*M14*) has a positive impact on the interest in hand tractors (*M15*), it also implies that the gender (*B1*) has a positive impact indirectly on the interest in hand tractors (*M15*) through the interest in farming jobs (*M14*).

There are some hypothesized paths that do not have a significant relationship in the proposed conceptual model, such as the economic outcome from farming (*M13*), which is hypothesized as having a positive impact on the farming jobs interest. It implies that the economic factor does not contribute significantly to the student interest in hand tractors variable in the region. The other insignificant relationship is the risk perception (*M10_M12*), which is hypothesized as having a negative impact on the interest in farming jobs.

The negative value of coefficient results in Eqs. (13) and (14) show that the risk perception has a negative impact on the interest in farming jobs. However, a significant relationship is not identified. It also happens to the *F* variable (force labor percentage work in farming or farmer in the place that the student lives), which hypothesizes that more inhabitants who live around the farming area would have a positive impact on the future job choice (*B3*) and on the interest in farming jobs (*M14*). Furthermore, there is a tendency for an opposite result from the hypothesized conceptual model. It is shown in negative value of *F* coefficient in the Eq.13 and 14 that the greater force labor working in farming effects does not affect the greater interest in farming jobs in regard to the student perception. It tends to support a negative perception of farming jobs in the region that farming is not a good career in the future (Mundlak *et al.*, 2002).

The decomposing correlations are enhanced to identify how big the effect of the significant independent variables is totally to the dependant variable (the interest to hand tractor) of the direct and the indirect effect. The total effect was obtained from the total coefficient of direct effect and indirect effect of the independent variables to the dependent variable by multiplying the significant path coefficients with partial correlation coefficients (Pearson zero order correlation). Overall, 40.13% of the hand tractor interest is explained by the set of significant predictors. The direct effects of the gender variable, the interest in farming jobs, and the future job choice perception account for 6.96%, 23.41%, and 4.66% respectively. The indirect effect of the gender variable accounts for 5.1% of the interest in hand tractors through the interest in farming jobs.

4.2 The Neuro-fuzzy Models

4.2.1 The Neuro-fuzzy Model on Farming Jobs Interest

The neuro-fuzzy model on farming jobs interest identification uses the independent variables used in the path analysis model, which are *B1, B2, B3, F, M1_M9, M10_M12,* and *M13* as the input variables and the *M14* as the output variable (Table 1). The neuro-fuzzy model calculates all variables and identifies the best selected predictor variables input to the interest in farming jobs based on errors (RMSE) as shown in Table 3.

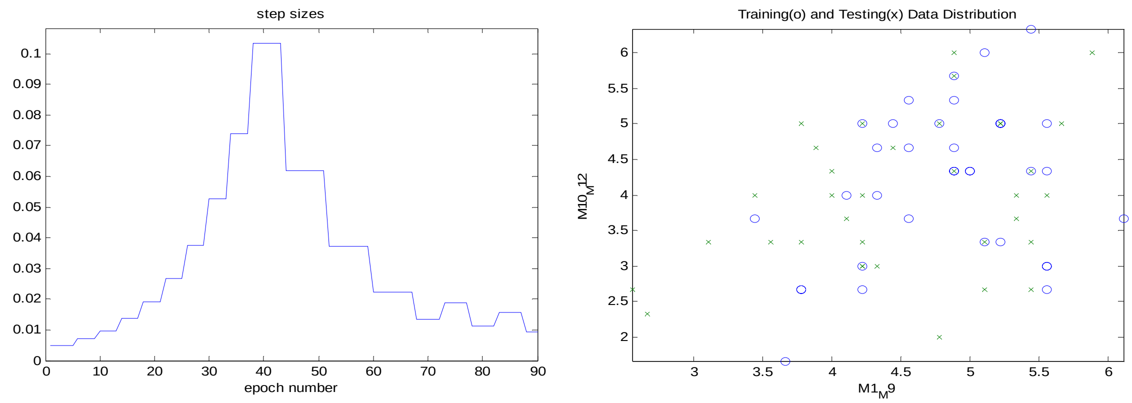
Table 3. The best selected predictor variables of farming jobs interest

Number of variables predicted	Farming jobs predictor variables	Training error	Testing error
One variable	*M10_M12*	1.504	1.891
Two variables	*M10_M12* and *M1_M9*	1.234	1.973
Three variables	*M10_M12*, *M1_M9*, and *M13*	0.696	11.469

The three best selected predictor variables (*M10_M12, M1_M9 and M13*) gain the lowest training error but the testing error is too high. The best selected variable found is *M10_M12* or the risk perception, which has more prediction power than others. However, in order to find the more reliable selected variables, the *M10_M12 and M1_M9* as the two input predictor variables are expanded to reach the lower error. Then the model is extended for 90 epochs by setting the step sizes, increase rate, decrease rate, and some parameters of fuzzy inference. The step sizes are shown in Figure 6 (a). The results show that testing error is 1.613, at which the training error is 1.271. It shows the more reliable inputs in comparison to the results of linear regression of all independent variables, which shows that the error for testing data is 1.639 and for training data is 1.571 by the least-squares method.

The problem as shown in Figure 6 (b) is the lack of data distribution that influences the variability of setting the inference system to the lowest error of training and testing. This is the problem of grid partitioning, which actually is needed for the first-order Sugeno fuzzy model (Jang *et al.*, 1997). Otherwise, the neuro-fuzzy model of choosing the two most relevant inputs has lower error than the linear regression, though the input value is only two from seven in linear regression. It means that the neuro-fuzzy model can reduce the input variable well.

The results explain the important of the risk perception as the one input of best predictor to the interest in farming jobs, which explains the unwillingness of the people to accept risks (Shanteau & Ngui, 1989) and as a reason why an unpredictable condition such as farming jobs are not interesting to the young people.



(a) (b)

Figure 6. (a) The step sizes on farming jobs interest prediction variable using *M1_M9* and *M10_M12* variables; (b) The training and data distribution of *M1_M9* and *M10_M12* variables.

4.2.2 The Neuro-fuzzy Model on Farm Machine Interest

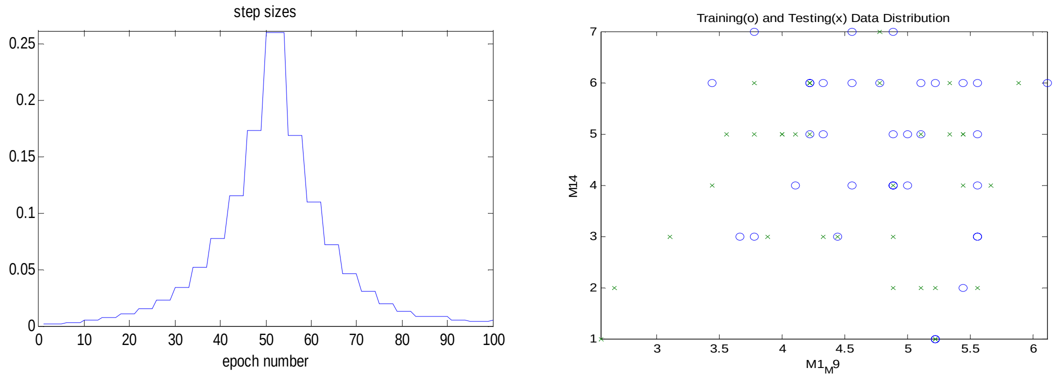
The model used *B1, B2, B3, F, M1_M9, M10_M12, M13*, and *M14* (Table 1) as the input or the independent variables and the *M15* as the output or the dependent variable. The neuro-fuzzy modeled identifies the best selected predictor variables input to the interest in hand tractors as in Table 4. The three best selected variables gain the lowest training error, but the problem is at which the testing error is too high. The best selected variable reveals that *M14* has more prediction power than other variables based on the testing error gained. It is a reliable result and supports the result of path analysis. It explains the close relationship of student interest in hand tractors to farming jobs interest as meaning that the people interested in farming jobs account hand tractors in their work in farming.

Table 4. The best selected predictor variables of hand tractor interest

Number of variables predicted	Farming jobs predictor variables	Training error	Testing error
One variable	*M14*	1.690	1.594
Two variables	*M14* and *M1_M9*	1.478	3.497
Three variables	*M14*, *M1_M9*, and *F*	0.765	14.410

The extended model is continued to identify the more selected variables by setting the step sizes, increase rate, decrease rate, and some parameters of fuzzy inference. The step sizes are shown in Figure 7 (a). After 100 epochs the minimal testing error is 1.774, at which the training error is 1.355. Linear regression of all independent variables to the hand tractor interest variable gains a testing error of 1.927 and a training error of 1.641. The lack of data distribution interferes with the fuzzy inference setting as shown in Figure 7 (b), but the results give lower error than the linear regression, which is reliable.

The load of overall farming jobs perception as the best selected predictor to the interest in hand tractors besides the farming jobs interest proves that it is important for the ease of activity on farming development using hand tractors on decreasing the drudgery (So *et al.*, 2001). It implies the importance of considering the behavioral side in farm mechanization development by developing the hand tractor that people are interested in.



(a) (b)

Figure 7. (a) The step sizes on hand tractor interest prediction using *M1_M9* and *M14* variables. (b) The training and data distribution of *M1_M9* and *M14* variables.

The neuro-fuzzy models make it easier to analyze the relationship of the independent variables to the target by considering the most powerful predictor variable data on the interest prediction (dependent variable). The behavioral interest models for farming jobs and hand tractors represent the nonlinear relationship, which is not easy to predict linearly. Thus, the neuro-fuzzy system has superiority in performing predictions such as this, which are proven by the results gained. The developed model framework supports the decision maker in minimizing the number of input variables, representing the nonlinear variability of perception and behavioral characteristics, and predicting the level of interest reliably.

5. CONCLUSIONS

The path analysis model identifies that the direct positive predictor variable of the interest in farming jobs *(M14)* is the gender variable (*B1*). It also identifies that the direct positive predictor variables of the interest in hand tractors *(M15)* are the interest in farming jobs (*M14*), the willingness to take jobs related to farming (B3), and the gender *(B1)* variables, which account for 6.96%, 23.41%, and 4.66%, respectively, of the total effect. It is also identified that the gender variable *(B1)* is the indirect predictor variable through the interest in farming jobs variable (*M14*), which accounts for 5.1% of the total effect.

The neuro-fuzzy model of farming jobs identifies that the most important prediction variable of farming jobs for one input variable is the risk perception (*M10_M12*), and for two input variables are the risk perception (*M10_M12*) and the ease perception of the load of overall farming activities (*M1_M9*). The neuro-fuzzy model of hand tractor interest identifies that *M14* (the interest in farming jobs) is the most important prediction variable for one input, and for two input are the interest in farming jobs (*M14*) and the ease perception of the load of overall farming activities (*M1_M9*).

This paper provides information regarding a behavioral study for contributing to farm mechanization development in a region. The path analysis model explains the relationship of each variable modeled effectively and calculates the account of predictor variables' effect to the dependant variable. The neuro-fuzzy models enhance the learning capability of the nonlinear data to obtain the least error of independent variables for being predictor variables with the benefit of human likeness setting of parameters' input for optimal identification. The best predictor variables with the least error may be used for the input of a behavioral decision support system using soft computing on mechanization policy development, such as a suitable or optimal farm machine selection system.

The practical application of the information gathered and the benefit of models may be illustrated as follows. The models extract data to obtain the important reliable variables. The information gathered is compared to the behavioral sides of other machines in the considered system. The official simulates the data by setting the objective's criteria of the qualitative and quantitative data of some considered variables. It may implement an enhanced neuro-fuzzy or an optimization algorithm. The output is a suitable selected farm machine, which fits the qualitative and quantitative criteria such as the people's interest, the cost, and the possible outcome.

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