P-ISSN: 2618-0723
E-ISSN: 2618-0731

NAAS Rating (2025): 5.04
www.extensionjournal.com

International Journal of Agriculture Extension and Social Development

Volume 8; Issue 9; September 2025; Page No. 249-252

Received: 05-07-2025
Accepted: 09-08-2025

Indexed Journal
Peer Reviewed Journal

Path analysis of knowledge of young farmers towards climate-smart agricultural interventions

SA Patel, YA Garde, N Tale and OP Sharma

KVK, NAU, Navsari, Gujarat, India

DOI: https://www.doi.org/10.33545/26180723.2025.v8.i9d.2408

Corresponding Author: SA Patel

Abstract

The present study employed path analysis to examine the causal influences of selected independent variables on the knowledge of young farmers regarding Climate-Smart Agriculture (CSA) interventions. While correlation and regression analyses reveal relationships and combined effects among variables, path analysis enables identification of both direct and indirect causal influences, thereby offering deeper insights into the dynamics of farmers' knowledge and attitudes. Twelve independent variables that showed significant correlations with dependent variables were included in the analysis, with data collected from 280 respondents. The results revealed that leadership ability exerted the maximum positive direct effect (0.180) on knowledge, followed by annual income, mass media exposure, scientific orientation, and risk orientation, while land holding (-0.026) showed the largest negative direct effect. In terms of total indirect effect, leadership ability again exerted the strongest positive influence (0.209), whereas land holding (-0.006) showed a negative effect. Substantial indirect effects highlighted awareness of climate change (0.050 through leadership ability) as the strongest positive influence and mass media exposure (-0.025 through leadership ability) as the strongest negative influence. Overall, the findings suggest that enhancing leadership ability, awareness on climate change, education, annual income, and decision-making skills can significantly improve young farmers' knowledge of CSA interventions. The study underscores the importance of leadership development and capacity building as pivotal strategies for strengthening farmers' knowledge systems in the context of climate-smart agriculture.

Keywords: Climate smart agricultural interventions, path analysis, knowledge, young farmers

1. Introduction

Agriculture in the twenty-first century faces the dual challenge of producing more food for a rapidly growing population while adapting to the impacts of climate change. Rising temperatures, erratic rainfall and extreme weather events have increased risks and vulnerabilities across farming systems, particularly in developing countries such as India (Aggarwal, Vyas, Thornton, Campbell, & Kropff, 2019; Thornton *et al*., 2018) [1, 19]. India's predominantly agrarian economy is highly sensitive to climate variability, which threatens food security and rural livelihoods. To address these challenges, Climate-Smart Agriculture (CSA) has been promoted as an integrated approach that simultaneously aims to enhance productivity, strengthen resilience, and reduce greenhouse gas emissions (Food and Agriculture Organization [FAO], 2013; Lipper *et al*., 2014) [5, 10].

CSA encompasses a wide range of interventions, including improved crop varieties, resource-efficient practices, soil and water conservation measures, and institutional innovations. However, the success of CSA depends not only on the availability of these interventions but also on the knowledge, awareness and attitudes of farmers, particularly the youth, who represent the future of agriculture (Patel & Sharma, 2022; Singh, Wani, Anantha, Sudi, & Devraj, 2019) [14, 15]. Young farmers are often more innovative, adaptive and willing to experiment with new technologies, making their knowledge and attitudes central to the widespread adoption of CSA (Bryan *et al*., 2013; Mertz, Mbow, Reenberg, & Diouf, 2009) [3, 12].

Knowledge is a critical factor that shapes farmers' decision-making and adoption behaviour. It is influenced by a complex interplay of socio-economic, psychological and communicational variables (Rogers, 2003; Meena, Singh, & Singh, 2014) [17, 11]. Empirical studies have highlighted the role of education, farm income, extension contact, leadership ability, innovativeness, and risk orientation in determining farmers' knowledge levels (Kadian, Singh, & Kumar, 1997; Sharma, Singh, & Meena, 2018) [8, 18]. Among these, leadership ability has been consistently emphasized as a key determinant of knowledge diffusion and collective decision-making in rural communities (Katungi, Edmeades, & Smale, 2007; Rogers, 2003) [9, 17]. Likewise, access to information through mass media and extension systems has been found to accelerate knowledge acquisition and adoption of climate-smart practices (Mittal & Mehar, 2016; Singh *et al*., 2019) [13, 15].

Despite the recognition of these factors, disentangling their effects on knowledge remains complex. Traditional correlation analysis provides simple associations, while regression analysis measures combined effects, but neither approach allows for examining causal ordering or distinguishing between direct and indirect influences (Garson, 2014) [7]. Path analysis, however, provides a more

refined method by partitioning the effects of independent variables into direct, indirect, and total effects, thereby enabling researchers to understand the causal mechanisms more clearly (Alwin & Hauser, 1975; Fidelis & Sunday, 2018) [2, 6]. Originally developed in the social sciences, path analysis has been increasingly applied in agricultural extension research to model knowledge systems and adoption dynamics (Crossman, 2020) [4].
In India, path analysis has proven valuable in identifying the socio-economic and psychological determinants of technology adoption. Sharma *et al*. (2018) [18], for instance, demonstrated how decision-making ability and risk preference exert significant indirect effects on adoption of improved practices through mediating variables such as leadership ability. Patel and Sharma (2022) [16] found that leadership ability and awareness of climate change were the strongest predictors of young farmers' knowledge of CSA interventions in Gujarat. Such findings highlight the utility of path analysis for unpacking complex relationships that shape farmers' adoption behaviour.
South Gujarat offers a relevant case for this research due to its diverse agro-climatic conditions, intensive cropping systems, and vulnerability to climate-induced risks such as salinity ingress, erratic monsoons, and floods. At the same time, the region is home to progressive farming communities and a strong extension network, making it a fertile ground for analyzing how young farmers acquire and apply knowledge on CSA. Given that Gujarat has been a leader in agricultural innovation and growth in India, the lessons drawn from this region can provide valuable insights for scaling CSA practices nationally.
Therefore, the present study was undertaken with the objective of examining the direct and indirect effects of socio-economic, psychological, and communication factors on the knowledge of young farmers toward CSA interventions in South Gujarat. By applying path analysis, the study identifies the variables that most strongly influence knowledge levels and reveals the pathways through which these effects occur. The findings are expected to guide policymakers, extension workers, and researchers in designing targeted interventions that enhance leadership, decision-making, and awareness, thereby empowering young farmers to act as agents of climate resilience.

2. Research methodology

The study was conducted in South Gujarat during 2022 using an ex-post-facto research design (Robinson, 1976), as the independent variables had already occurred or were not manageable. A multistage sampling technique was adopted wherein all seven districts of South Gujarat were purposively selected, from each district two talukas were chosen randomly, and from each taluka 20 young farmers were randomly selected, making a total sample of 280 respondents. Data were collected through a pre-tested interview schedule at farmers' homes or fields and analyzed using correlation coefficient (r) and path analysis to assess the direct, indirect, partial, and total influence of independent variables on the dependent variables, with a linear regression model applied to study the relationships.

2.1 Path analysis

Path analysis is a widely used technique for modeling plausible sets of causal relations among three or more observed variables. In the social sciences path analysis has been widely used especially in sociology, and also in psychology (Crossman, 2020) [4].
A path model can include any number of independent (or exogenous) variables, any number of dependent (endogenous) variables, and any number of intermediate variables, which are both dependent on some variables and predictive of others. In a path diagram, each variable is represented. The hypothesized links among variables are shown by arrows, representing predictive or correlational relations.
The path coefficients were obtained by solving a set of simultaneous equations as below (Fidelis and Sunday, 2018) [6]:

$$r_{ny}=P_{ny}+r_{n2}P_{2y}+r_{n3}P_{3y}+r_{n4}P_{4y}+\ldots+r_{nx}P_{xy}$$

Where,
r_{ny} = Correlation coefficient between one component item and dependent variable 'y'
P_{ny} = Path coefficient between one item and 'y'
r_{n2}, r_{n3}, r_{nx} = Correlation coefficient between item and other item component in tern
The following correlation matrix was formed:

Matrix - A Matrix - B Matrix - C

$$\begin{bmatrix} r_1y \\ r_2y \\ r_3y \\ . \\ . \\ r_ny \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & . & . & r_{1n} \\ r_{21} & r_{22} & r_{23} & . & . & r_{2n} \\ r_{31} & r_{32} & r_{33} & . & . & r_{3n} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ r_{n1} & r_{n2} & r_{n3} & . & . & r_{nn} \end{bmatrix} \text{x} \begin{bmatrix} p_1y \\ p_2y \\ p_3y \\ . \\ . \\ p_ny \end{bmatrix}$$

Where,
$r_{12} = r_{21}$ and so on
r_{1y} = Correlation between first component item and dependent variable '*y*'
Path coefficient (P_{ij}) was obtained as follow:

$$P_{iy} = (B^{-1}) \times (A)$$

Where, (B^{-1}) = The inverse of correlation matrix of items
The indirect effects for a particular item through other items were obtained by multiplication of direct path and particular correlation coefficient between those two items, respectively.

Indirect effect = $r_{ij} \times P_{iy}$

Where, i =1, 2, 3, ……, n
j = 1, 2, 3, ……, n
$P_{iy} = P_{1y} \times P_{2y} \times P_{3y} \times \ldots \ldots \times P_{ny}$

The residual factor which represents the variation in field unaccounted for this association was calculated from the following formula:

$$\text{Residual effect} = U = \sqrt{1 - \sum p_{iy} r_{iy}}$$

Where, $R^2 = \sum p_{iy} r_{iy}$

3. Results and Discussion

The path analysis is a very useful tool for assessing the causal influences of a set of independent variables on dependent variables. Direct and indirect effects can be known of individual independent variables on dependent variable.

For the purpose of using path analysis in the present study, only those independent variables were selected which had significant correlation with dependent variables, i.e. knowledge and attitude of young farmers towards CSA interventions. The results are presented in tables 1 and diagrammatically depicts through fig. 1.

Table 1: Path coefficient showing the direct, total indirect and substantial indirect effects of independent variables on knowledge (n=280)

Sr. No.	Independent variables	Direct effect	Total indirect effect	Substantial indirect effect through	
				1	2
1.	X_1 Education	0.075	0.119	0.016(X_4)	0.013(X_{11})
2.	X_2 Land holding	-0.026	-0.006	0.012(X_8)	-0.007(X_4)
3.	X_3 Annual income	0.122	0.168	0.012(X_{12})	0.009(X_7)
4.	X_4 Mass media exposure	0.116	0.121	-0.025(X_{11})	0.011(X_1)
5.	X_5 Extension contact	0.069	0.122	0.014(X_{11})	0.012(X_9)
6.	X_6 Scientific orientation	0.093	0.140	0.012(X_4)	0.009(X_3)
7.	X_7 Awareness on climate change	0.067	0.139	0.050(X_{11})	0.014(X_3)
8.	X_8 Innovativeness	0.087	0.116	0.015(X_{11})	-0.011(X_1)
9.	X_9 Risk orientation	0.089	0.126	-0.015(X_{11})	0.011(X_1)
10.	X_{10} Risk preference	0.042	0.174	0.025(X_4)	0.024(X_{11})
11.	X_{11} Leadership ability	0.180	0.209	0.014(X_7)	0.014(X_{12})
12.	X_{12} Decision making ability	0.051	0.147	0.021(X_7)	0.014(X_{11})
Residual: 0.85177					

3.1 Direct effect

The data presented in table 1 and fig. 1 reveals that leadership ability had exerted maximum direct positive effect (0.180) followed by annual income (0.122), mass media exposure (0.116), scientific orientation (0.093), risk orientation (0.089), innovativeness (0.087), education (0.075), extension contact (0.069), awareness on climate change (0.067), decision making ability (0.051) and risk preference (0.042). As far as negative direct effect is concerned land holding (-0.026) had exerted maximum direct negative effect on knowledge of young farmers about CSA interventions.

From the above results, it can be concluded that the independent variable leadership ability exerted highest positive direct effect on knowledge whereas, land holding exhibited largest negative direct effect on knowledge of young farmers about CSA interventions.

3.2 Total indirect effect

The data presented in table 1 and fig. 1 reveals that, the total indirect effect is concerned, 11 variables had positive total indirect effect on knowledge of young farmers about CSA intervention. Furthers, it can be observed that leadership ability had maximum total indirect effect (0.209) followed by risk preference (0.174), annual income (0.168), decision making ability (0.147), scientific orientation (0.140), awareness on climate change (0.139), risk orientation (0.126), mass media exposure (0.121), extension contact (0.122), education (0.119) and innovativeness (0.116). As far as negative direct effect is concerned land holding (-0.006) had exerted maximum total indirect negative effect on knowledge of young farmers about CSA interventions.

From the above results, it can be concluded that the independent variable leadership ability exerted highest positive total indirect effect on knowledge whereas, land holding exhibited largest negative total indirect effect on knowledge of young farmers about CSA interventions.

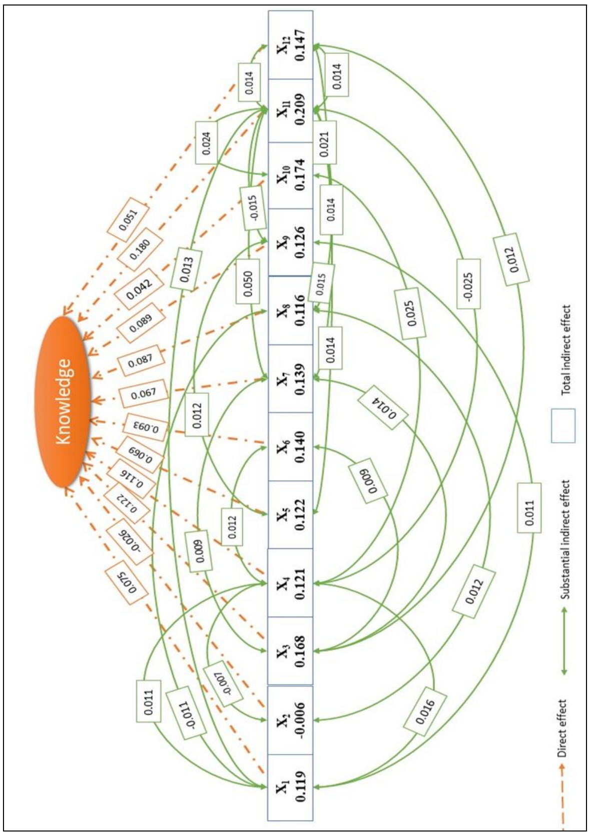

Fig 1: Direct, total indirect and substantial indirect effects of independent variables on knowledge

3.3 Substantial indirect effect

The data presented in table 1 and fig. 1 reveals that out of 24 substantial indirect effects, eight each routed through leadership ability, four each routed through mass media exposure, three each routed through education and awareness on climate change, two each routed through innovativeness, annual income, decision making ability and one each routed through risk orientation.

With regards to substantial indirect effect, the first substantial negative indirect effect on respondents was put forth by mass media exposure (-0.025) through leadership ability followed by risk orientation (-0.015) through leadership ability, innovativeness (-0.011) through education, however, first substantial positive indirect effect on respondents was put forth by awareness on climate change (0.050) of young farmers through leadership ability followed by risk preference (0.025) through mass media exposure and risk preference (0.024) through leadership ability of young farmers.

The variable mass media exposure (-0.025) exhibited highest negative substantial indirect effect on knowledge through leadership ability.

The variable awareness on climate change (0.050) exerted the highest positive substantial indirect effect on knowledge through leadership ability.

From the above results, it can be concluded that the variable leadership ability exerted highest positive direct effect on knowledge. Regarding total indirect effect, the variable leadership ability exerted highest positive total indirect effect on knowledge. While, the awareness on climate change exerted the highest positive substantial indirect effect on knowledge through leadership ability. The variables education, annual income, mass media exposure, innovativeness, risk orientation, leadership ability and decision making ability were the key variables providing a way for all other independent variables in exerting their substantial indirect effect on knowledge. This naturally suggests that positive increase in education, annual income, mass media exposure, awareness on climate change, innovativeness, risk orientation, leadership ability and decision making ability would bring the substantial change in knowledge.

4. Conclusion

It is evident from the results of the path analysis that the variable leadership ability had exerted highest positive direct effect on attitude and the variable risk preference had exerted highest positive total indirect effect on attitude. While, decision making ability had exerted the highest positive substantial indirect effect on attitude through leadership ability, the higher effect of these variables with the level of attitude indicates that the young farmers with leadership ability, risk preference and decision making ability were likely to influence the level of attitude to great extent.

5. Implication

Extension worker, policy maker and other line departments shall consider these attributes which help to effectives outcome of new policies pr scheme for further development of young farmers.

6. Consent

As per the international standard or university standard, respondents written consent has been collected and preserved by the author(s).

7. Competing Interest

Authors have declared that no competing interests exist.

References

1. Aggarwal PK, Vyas S, Thornton P, Campbell BM, Kropff M. Importance of considering technology growth in impact assessments of climate change on agriculture. Glob Food Secur. 2019;23:41-8.
2. Alwin DF, Hauser RM. The decomposition of effects in path analysis. Am Sociol Rev. 1975;40(1):37-47.
3. Bryan E, Ringler C, Okoba B, Roncoli C, Silvestri S, Herrero M. Adapting agriculture to climate change in Kenya: Household strategies and determinants. J Environ Manag. 2013;114:26-35.
4. Crossman A. Understanding path analysis. ThoughtCo. 2020. https://www.thoughtco.com/path-analysis-3026444.
5. FAO. Climate-smart agriculture sourcebook. Food and Agriculture Organization of the United Nations; 2013.
6. Fidelis E, Sunday O. Application and relevance of path analysis in causal modelling. Glob J Arts Humanit Soc Sci. 2018;6(10):26-50.
7. Garson GD. Path analysis. Statistical Associates Publishers; 2014.
8. Kadian KS, Singh R, Kumar R. Adoption of dairy innovations by rural women. Indian J Dairy Sci. 1997;50(6):477-82.
9. Katungi E, Edmeades S, Smale M. Gender, social capital and information exchange in rural Uganda. IFPRI Discussion Paper 00746. International Food Policy Research Institute; 2007.
10. Lipper L, Thornton P, Campbell BM, Baedeker T, Braimoh A, Bwalya M, *et al*. Climate-smart agriculture for food security. Nat Clim Change. 2014;4(12):1068-72.
11. Meena MS, Singh KM, Singh RKP. Farmer's knowledge index and adoption of new technology in Bihar. Indian J Ext Educ. 2014;50(3&4):44-8.
12. Mertz O, Mbow C, Reenberg A, Diouf A. Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. Environ Manag. 2009;43(5):804-16.
13. Mittal S, Mehar M. Socio-economic factors affecting adoption of modern information and communication technology by farmers in India. Agric Econ Res Rev. 2016;29(2):167-78.
14. Patel SA, Sharma OP. Scale on Attitude of Young Farmers Towards Climate Smart. 2022.
15. Singh RK, Wani SP, Anantha KH, Sudi R, Devraj R. Climate-smart farming systems: insights from a case study in southern India. J Agrometeorol. 2019;19(2):184-91.
16. Patel SA, Sharma OP. Knowledge of young farmers about climate-smart agricultural interventions. Int J Environ Clim Change. 2022;12(11):658-65.
17. Rogers EM. Diffusion of innovations. 5th ed. Free Press; 2003.
18. Sharma R, Singh S, Meena MS. Socio-psychological determinants influencing adoption of improved crop practices. Indian J Ext Educ. 2018;54(2):67-73.
19. Thornton PK, Ericksen PJ, Herrero M, Challinor AJ. Climate variability and vulnerability to climate change: A review. Glob Change Biol. 2018;20(11):3313-28