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Identifying and Understanding Factors Influencing the Knowledge Level of Farmers in Watershed Development Programme Using Principal Components Analysis

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Watershed Development Programmme is based on bottom-up planning and a participatory approach. It will be easier to implement the programme successfully and get the desired results if we have a good comprehension of the guidelines. On many different developmental programmes implementation its components including institutional arrangement, community organisation, objectives, programme creation and implementation, funding pattern, monitoring and evaluation,

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significant gaps were observed. These socio -economic factors provide essential information to support efforts and policies aimed at improving adoption by recognizing heterogeneities in the targeted populations. Principal component analysis (PCA) is a technique for reducing the dimensionality of datasets, increasing interpretability but at the same time minimizing information loss. The present study was conducted with a sample size of 192 progressive farmers and watershed user groups in Nuapada and Kalahandi district of Odisha state, aiming to identify the major socio economic factors governing farmers' knowledge and adoption level of different watershed activities. Three different principal components (PCs) could finally be extracted out of twelve relatively important variables governing knowledge and participation level of farmers in different watershed activities. These three factors were resource richness, which was associated with higher farm revenue, cosmopoliteness, which was associated with extended contact and motivation, and family type, which was associated with manpower and farming as a primary employment. Firstly, data reduction was conducted through principal component analysis to identify three important components accounting for 58.66% of the total variability in the data. It is evident from the results that socioeconomic factors such as Land holding, Annual Income, Type of house, Cosmo politeness and extension contact, Education, more use communication materials, Social participation and age of the farmer, can be associated with higher knowledge and adoption of watershed activities and practices. From the findings of the study, it was concluded that three principal components like 'resource richness', 'education and extension contact' and 'farm family occupation**"** were found to have exerted significantly high influence and contributed 23.44%, 20.12% and 15.1% variance respectively in determining the extent of farmers' knowledge level about watershed activities . These factors can be used as essential input to predict models or as benchmarks for developing scales or indices for measuring farmers' progressiveness and knowledge and adoption of watershed activities.

Keywords: Watershed development programme; socio economic factors; multivariate analysis dimension reduction technique; principal components analysis.

1. INTRODUCTION

Following the implementation of the new watershed guidelines from 2001 created by the Ministry of Rural Improvement and the "JANASAHABHAGITA" guideline of the Ministry of Agriculture, Government of India, a participatory watershed development programme was conducted in Odisha. Clearly defined institutional structures, operational procedures, programme designing, programme implementation, fund use, monitoring, and evaluation are all included in the guideline. Its foundation is just the idea of bottom-up planning with a single window, integrated, participative, and sustainable area development programme. "The goal of watershed management is to protect or conserve the hydrologic services the watershed provides while minimising or avoiding adverse downstream or groundwater impacts. Watershed management is the integrated use of land, vegetation, and water in a geographically discrete drainage area for the benefit of its residents" [1].

Dufera, et al [2] concluded that the overall findings indicated that, the intervention of watershed management practice not only increase crop yield and livestock production but also it has high contribution to increases the perception, adoption, participation, and maintenance of implemented watershed management practices. The watershed residents must actively take part in the programme, from design to implementation, budget usage, and activity evaluation [3-6]. As a result, a prerequisite for the programme's successful implementation is the watershed people's thorough awareness of operating procedure. The purpose of the current study is to evaluate the watershed people's level of understanding of how the programme operates in light of this premise. When examining the implementation of watershed practises in connected areas, the socioeconomic aspects of the farmers might be quite helpful. In a diverse population, adoption of watershed practises won't be improved by any one uniform strategy [7-10]. Therefore, it is imperative that initiatives and/or regulations designed to promote the adoption and use of watershed technologies and practises in rain-fed areas can therefore create new structures and strategies or modify their existing ones for improving adoption of watershed practices.

Farmers' progressivity, excellence, and success are typically influenced by a variety of separate influences, or determinants. The actual components are latent dimensions of multiple underlying variables. Therefore, a focus on quantitative research was made in the current study with the intention of identifying and prioritising the determinants of farmers' socioeconomic characteristics that influence progressiveness, resulting in higher adoption and, higher profit and overall success of watershed activities. This was done in order to have such a perspective of the farmers as well as other stakeholders [11]. “Socioeconomic status (SES) is an economic and sociological combined total measure of a person's work experience and of an individual's or family's economic access to resources and social position in relation to others. When analyzing a family's SES, the household income, education and occupation are examined, as well as combined income, whereas for an individual's SES only their own attributes are assessed” (Udiin et al .2014) .

(Chikowo et al. 2014) stated “household typologies based on socioeconomic characteristics that influence adoption technologies” and [12] who typified “farm households based on socioeconomic characteristics that promote adoption of new farming technologies in general”. Socio-economic status is the position an individual or a family occupies concerning the prevailing average standards of cultural possessions, effective income, material possession, and participation in the group activity of the community. "Knowledge is defined as those behaviors and test situations which emphasized the remembering either by recognition or recall of ideas, materials or phenomena" (Bloom et al, 1956). “In the present study, knowledge was operationalized as the quantum of specific information possessed by the respondents about the intervened technology In this study, the empirical approach adopts multivariate statistical techniques that allow us to identify the socio economic variables, especially when an in-depth database is available” [12], [13] and [12]. “Principal component analysis (PCA) is a multivariate technique that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables. Its goal is to extract the important information from the table, to represent it as a set of new orthogonal variables called principal components [14]. Principal component analysis (PCA) simplifies the complexity in high-dimensional data while retaining trends and patterns. It does this by transforming the data into fewer dimensions, which act as summaries of features.

A sequence of observations of possibly correlated variables are converted into a set of principal component values, which are variables that are linearly uncorrelated, in the statistical procedure known as principle component analysis (PCA). Principal component analysis is employed in exploratory data analysis and the development of prediction models. The first main component can also be defined as the path that maximises the variance of the forecasted data and the first principal component can equivalently be defined as a direction that maximizes the variance of the projected data. “The principal components are eigenvectors of the data's covariance matrix. Thus, the principal components are often computed by eigen decomposition of the data covariance matrix or singular value decomposition of the data matrix. PCA is the simplest of the true eigenvector-based multivariate analyses and is closely related to factor analysis” as reported by [15]. According to [16] “PCA is a multivariate statistical technique used to reduce the number of variables in a data set into a smaller number of ‘dimensions’. In mathematical terms, from an initial set of ‘ n ‘ correlated variables, PCA generates uncorrelated indices or components, where each component is a linear weighted combination of the initial variables. The weights for each principal component are given by the eigenvectors of the correlation matrix, or if the original data were standardized, the co-variance matrix. The variance for each principal component is given by the eigenvalue of the corresponding eigenvector” [17-20]. The components are ordered so that the first component. (PC_1) explains the largest possible amount of variation in the original data. The second component (PC_2) is completely uncorrelated with the first component, and explains additional but less variation than the first component, subject to the same constraint. Subsequent components are uncorrelated with previous components; therefore, each component captures an additional dimension in the data, while explaining smaller and smaller proportions of the variation of the original variables. The higher the degree of correlation among the original variables in the data, the fewer components required to capture common information.

1.1 Objective

The study was undertaken with an objective to assess the knowledge and perception level of the tribal people about functioning of Watershed development programme and use of principal component analysis (PCA) for necessary data reduction to identify essentially significant, socio economic variables. The knowledge and adoption level of the farmers depend upon the farmer's age, education, size of holding socio-economic status and their progressiveness because progressive outlook motivates the farmers to adopt the new ideas or agricultural technology for their economic gains.This study aims to categorize and focus on the dynamics of socio- economic characteristics in influencing the knowledge and adoption level of different watershed activities operating in the study area. Specifically, in this study combination of principal component analysis (PCA) was executed for necessary data reduction and cluster analysis to identify typical, socio economic variables affecting better implementation of the watershed development programme.

2. MATERIALS AND METHODS

The Western Undulating Agro-climatic Zone of Odisha, which includes the districts of Nuapada and Kalahandi, is where the study was conducted. For the investigation, six watersheds were chosen from two blocks in each district. A total of 192 people were chosen as responses, including the watershed president, secretary, chairman, six members of the user group, three people from the landless and women categories, and one member of the watershed committee for each watershed. With score values of 2, 1, and 0, respectively, the data obtained on the scale points of strongly agree, agree, and disagree were evaluated. The socio economic scale developed by [21] was used to measure the independent variables, including caste, education, land ownership, social involvement, and socioeconomic level. Mean score, gap percentage, multiple regression analysis and Principal component analysis (PCA) were employed to reveal the results. PCA is a statistical procedure that converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. In simpler words, PCA is often used to simplify data, reduce noise, and find unmeasured "latent variables". Principal Component Analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. Principal component analysis, or PCA, is a dimension reduction technique and a statistical procedure that allows us to summarize the information content in large data tables by means of a smaller set of "summary indices" that can be more easily visualized and analyzed. Principal Component Analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. PCA works on a process called Eigenvalue Decomposition of a covariance matrix of a data set. Principal component analysis was used for necessary data reduction analysis and it was evident from our results that various socioeconomic factors define clusters and can be associated with knowledge level of the respondents and adoption level of watershed practices.

Measurements may be made across a wide range of variables in some circumstances. However, it is impossible to manage many different variables. In order to explain the greatest amount of variation in the data, linear combinations that are ortho-normal and linearly independent are utilised in place of this many variables. Principal components are the names given to these linear combinations. By rotating the coordinate axes to create a new coordinate system with built-in statistical features, the original vector variable is transformed into the vector of principal components. The set of principle components produces a useful set of coordinates, and the component variances that go along with them describe the components' statistical characteristics. data.. The method of principal components is used to find the linear combinations with large variance. Firstly, "a principal components analysis (PCA) was conducted, a technique which is necessary to summarize the datasets into smaller and non-correlated dimensions or components" [16].

Prior to proceeding with the PCA approach, the Bartlett's test (Bartlett, 1950) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were performed to evaluate the appropriateness of the variables to be used as inputs to the PCA approach (Field, 2009). The Bartlett's test of sphericity checks the null hypothesis that the inter-correlation matrix came from a population in which the variables to be used in the PCA are all non-collinear. The results from this test using the survey data revealed a significant test (Chi-square = 884.901 and *p*-value = 0.000) suggesting that the variables are uncorrelated and hence suitable for a PCA. On the other hand, the KMO test compares the correlations and the partial correlations between the variables with a small KMO suggestive of highly correlated data. Using the Kaiser [22] characterization of the KMO values revealed that the study's KMO statistic of 0.748 is middling and suggestive of less correlated data. which all support the appropriateness of the analyzed data for the multivariate analysis procedures. The PCA approach followed the Kaiser criterion of retaining all the components with eigenvalues greater than one (1). Also, to simplify the interpretability of the PCA results, the components were rotated, using the Kaiser's normalization applicable when the number of variables does not exceed 30, which is the case with the analyzed data. This approach has also been applied in recent and related studies [12] and (Nainggolan et al. 2013). All the statistical analysis was conducted in SPSS version 19.0 and results were described in different subheads.

3. RESULTS AND DISCUSSION

The Watershed guideline envisages clear cut institutional arrangements, Community organization and objective of the programme, Operational procedure, Programme development, its implementation and monitoring aspects for effective implementation of the programme.

Comparative analysis of the knowledge as revealed from table-8 indicated that the knowledge level of the respondents of both Nuapada and Kalahandi district were at par. On several areas of the watershed development program's implementation, it was revealed that there were large gaps of 40.5 percent to 47.0 percent, with the largest gaps found in the funding pattern (47.0 percent). A disparity of 43.50 percent on average had indicated the need for additional exposure to the guidelines' in-depth comprehension.

Data from Table 1 revealed that all socioeconomic variables covered in the study, except for family type, family size, and occupation, corresponded to the level of knowledge of respondents in Nuapada district regarding effective implementation of the watershed program, showed a significant and positive impact. However, for the respondents from the Kalahandi district, knowledge level was positively influenced by education, extended contact, use of communication materials, and type of housing, while adversely influenced by occupation. The pooled mean score value showed that education, social participation, cosmopoliteness, extension contact, communication materials used, type of house, holding size, and annual income of the respondents were the significant factors accelerating the respondents' level of knowledge in the implementation of the watershed Development Programme.

The study also made an effort to evaluate the impact of socioeconomic factors raising respondents' knowledge levels toward successfully implementing the Watershed development programme.

The data in the table revealed that all the socio-economic variables covered under study had significantly and positively influenced the knowledge level of the respondents of towards effective implementation of the watershed programme. The information in the table 2 revealed that, with the exception of family type, family size, and occupation, all socioeconomic variables considered during the study had a significant and positive influence on the respondents of the Nuapada district regarding their level of knowledge regarding the effective implementation of the watershed programme. However, for the respondents from the Kalahandi district, knowledge level was positively influenced by education, extended contact, use of communication materials, and type of housing, while adversely influenced by occupation. The pooled mean score value showed that education, social participation, cosmopoliteness, extension contact, communication materials used, type of house, holding size, and annual income of the respondents were the important variables accelerating the respondents' level of knowledge in carrying out the watershed Development Programme.

The Pearson's Coefficient of correlation (r) value indicated that variables like education, social participation, cosmopoliteness, extension contact, communication materials used, type of house, holding size and annual income of the respondents were the essential variables accelerating the knowledge level of the respondents in implementation of the watershed Development Programme . Similar results were reported by Gautam and Shahare [23], who found that while age was negatively and significantly correlated with intervention technology adoption, respondents' education, size of holding social participation, and socioeconomic status were all positively associated with increased knowledge and adoption levels.

Concerning farming experience, as the age of the household head increases, the household acquires more farming experience, becomes more risk averse and diversifies its production [24] which can increase its appetite for new technology. Positive and significant correlations between socioeconomic status, the size of the holding, and attitude ratings have also been documented [25].

The education of the farmer and technology adoption have a positive correlation that is well acknowledged in the adoption literature by [26]. Farmers who have received greater education are predicted to be able to relate technology activities to their daily lives and to accept technology more quickly [27].

Table 1. Comparative analysis of the knowledge level of the respondents

Sl. No.	Knowledge	Mean Score			C.R. value	Pooled mean score (N=192)	Gap (%)
		Nuapada district (N=96)	Kalahandi district (N= 96)	Diff. (%)			
1	Institutional arrangement	0.94	1.26	25.40	0.148	1.10	45.00
2	Community organization	1.13	1.25	9.60	0.053	1.19	40.50
3	Objective	1.11	1.25	11.20	0.063	1.18	41.00
4	Operational procedure	1.17	1.09	6.84	0.037	1.13	43.50
5	Programme development	1.07	1.22	12.30	0.068	1.15	42.50
6	Programme implementation	1.19	1.11	6.72	0.036	1.15	42.50
7	Funding pattern	1.00	1.11	9.91	0.052	1.06	47.00
8	Monitoring and evaluation	1.10	1.04	5.45	0.028	1.07	46.50
	Average	1.09	1.17	6.84	0.037	1.13	43.50

Table 2. Influence of socio-economic variables on knowledge level of respondents

Variable	Nuapada district (n=96)		Kalahandi district (n=96)		Pooled mean score,(n=192)	
	'r' value	't' value	'r' value	't' value	'r' value	't' value
Age (X1)	0.392*	4.131	-0.131	-1.281	0.172	2.407
Education (X2)	0.552**	6.418	0.380*	3.983	0.470**	7.340
Family type (X3)	-0.086	-0.837	-0.103	-1.004	-0.059	-0.815
Family size (X4)	0.041	0.398	0.184	1.815	0.117	1.624
Social participation(X5)	0.301*	3.060	0.180	1.774	0.257*	3.666
Cosmopoliteness (X6)	0.480**	5.305	0.167	1.642	0.375*	5.576
Extension contact (X7)	0.687**	9.166	0.415**	4.422	0.581**	9.840
Communication material use (X8)	0.526**	5.996	0.516**	5.840	0.515**	8.281
Type of house (X9)	0.216*	2.145	0.243*	2.429	0.238*	3.378
Land holding (X10)	0.431**	4.631	0.118	1.152	0.301*	4.351
Occupation (X11)	-0.141	-1.381	-0.348*	-3.599	-0.195	-2.740
Annual Income(X12)	0.357**	3.705	0.056	0.544	0.210*	2.961

** Significant at 0.05 level of probability, ** Significant at 0.01 level of probability*

Watershed management enhanced agricultural output and household income while preserving environmental sustainability and ecological function. Farmers in micro-watersheds of these two districts have embraced a mixed farming strategy that combines agricultural cultivation with animal husbandry. Results showed that farm size and farming experience had a significant impact on adoption of watershed activities at ($p<0.05$) and a favourable relationship with natural resource use, employment earning by salary, vegetable production, and off-farm activities, which were the primary sources of household incomes for respondents [2].

For farming communities, access to agriculture extension services is another crucial information source. In order to translate research findings into a language and format that farmers can understand, agricultural extension officers connect farmers with research. Additionally, they give the researchers input from farmers. It suggests that access to extension services and their regularity may play a significant role in determining how quickly people adopt new technology. Several studies have reported use of extension services as an important determinant of technology by (Tizale, 2007). Empirical studies have found arable land size to be an important determinant of farm technology adoption [28].

Resource endowments (e.g. farm assets and other equipment) can influence farming technology adoption at household level [4]. Households who own or have access to resources are more likely to have increased chances and ability to adopt new technologies. So far as land holding is concerned, it seems to have positive association with economic motivation which was found to be statistically significant. The size of holding affects the state of economic motivation. It may be due to the fact that almost all were small and marginal land holders and engaging themselves in intensive cultivation. They want to earn more income from limited area. This indicated the positive association between the variables [29]. The education level, income from agriculture, farmer cooperative and credit were determinant factors for adoption of most of the agricultural practices [30] .

Economic incentive has been found to be significantly correlated with age, land ownership, and socioeconomic position. The statistically significant link between land ownership and economic motivation is positive The size of holding affects the state of economic motivation. Socio-economic status was significantly associated with economic motivation. Economic motive was strongly correlated with socioeconomic level. Good socio- economic status acts as supplementary factor to influence state of motivation regarding good earnings as reported by [29]. “Similar findings were reported by [31], stated that there was significant relationship between land size, age and education with the farmer's decision to adopt technologies in farm forestry . “The age of the farmer affected the farmer's knowledge and the awareness of the activities in the surrounding environment among other farmers.” Similar findings were reported by [23] and it was revealed that socioeconomic characters like education, caste, size of holding, social participation, socioeconomic status, and annual family income were positively and significantly correlated with attitude scores towards intervened technology. The above Table 2, further shows that age was found to be significantly associated but in a negative direction with the knowledge level of the respondents. A negative and significant association between age and knowledge level of the respondents indicated that relatively the elderly respondents had neutral to un favourable attitudes towards watershed technologies. It's possible that this is the case since elderly individuals tend to be conservative and tradition-bound. The knowledge level of farmers was found to be favourably and strongly correlated with education, and education generally alters a person's outlook, enabling him to absorb new technologies and change his attitude.

Additionally, attempts have been made to use multiple regression analysis to determine the causal factors that influence the respondents' level of knowledge as well as to identify significant socioeconomic variables and determine the causal relationship between those variables and the subsequent factors. The results obtained from the multiple regression analysis have been reflected in Table – 3.

It was revealed from Table 3 that the best fitted regression analysis could account for 46.50 percent of the total variance impacting the respondents' level of knowledge. Extension contacts, holding size, occupation, income, use of communication materials, and family size were among the twelve characteristics that significantly influenced the respondents' understanding of how to implement the Watershed Development Programme.

Table 3. Regression Analysis of socio economic variables on knowledge (n =192)

Variables	Un standardized Co-efficient		Standardized Co-efficient		't' value	Significance
	Beta	Std. Error	Beta	Std. Error		
Age (X1)	3.121	1.983	0.093	0.045	1.573	0.117
Education (X2)	0.933	1.194	0.061	0.081	0.781	0.435
Family type (X3)	-1.668	2.648	-0.040	0.071	-0.630	0.529
Family size (X4)	5.379	2.619	0.132	0.052	2.053	0.041
Social participation(X5)	0.477	0.590	0.049	0.045	0.808	0.419
Cosmopoliteness (X6)	-0.224	0.421	-0.039	0.079	-0.533	0.594
Extension contact (X7)	2.295	0.423	0.424	0.081	5.421	0.000
Communication material (X8)	1.059	0.532	0.173	0.058	1.989	0.048
Type of house (X9)	-0.544	1.896	-0.023	0.083	-0.286	0.774
Land holding (X10)	5.883	1.682	0.302	0.067	3.497	0.000
Occupation (X11)	-5.732	2.182	-0.155	0.065	-2.626	0.009
Annual Income (X12)	-4.198	1.756	-0.228	0.062	-2.390	0.017

R^2: 0.465 Adj.R^2: 0.429 S.E. : 14.846

3.1 PCA Data Analysis and Results and Discussions

The results from the KMO and Bartlett sphericity test showed that the variables under study are related justifying the use of PCA. A total number of 12 variables from 192 respondents were included in PCA study and, the overall KMO was greater than 0.5 (0 .748), while the Bartlett's sphericity test was significant (*p*-value = 0.000).

The goal of the PCA methodology is to decrease the number of variables; this method is frequently referred to as a "data reduction" or "dimension reduction" strategy. This basically means that we start off with a collection of variables and end up with fewer, but still significant, numbers of variables that capture the essence of the data in the initial dataset. The variability within and co-variation among variables, also known as the variance and co-variance, are taken into account when measuring the amount of "information contained" (i.e. correlation).

Either the reduction may come from finding that a specific linear computation of our variables explains a significant portion of the total variability in the data, or it could come from finding that some of the variables represent another "latent variable." The following output has been generated in SPSS a Varimax Rotation. Varimax rotation is a way of transforming the solution so that Rotated Component Matrix is relatively easy to understand. In particular, it identifies a solution where, to the maximum extent possible, correlations in the rotated component matrix are close to 1, -1 or 0.

Table 4. PCA -Descriptive Statistics

PCA -Descriptive Statistics			
Variables	**Mean**	**Std. Deviation**	**Analysis(N)**
Age (X1)	2.2656	.58539	192
Education (X2)	3.0990	1.28853	192
Family type (X3)	1.3281	.47076	192
Family size (X4)	1.6250	.48539	192
Social participation(X5)	5.8854	2.03565	192
Cosmopoliteness (X6)	10.1823	3.40512	192
Extension contact (X7)	5.1094	3.63714	192
Communication material (X8)	6.6042	3.21638	192
Type of house (X9)	2.5990	.83797	192
Land holding (X10)	2.6198	1.01105	192
Occupation (X11)	1.5885	.53415	192
Annual Income(X12)	2.0104	1.06829	192

Table 5. Extraction Method: Principal Component Analysis. Communalities

Communalities		
Variables	**Initial**	**Extraction**
Age (X1)	1.000	.353
Education (X2)	1.000	.646
Family type (X3)	1.000	.569
Family size (X4)	1.000	.526
Social participation(X5)	1.000	.485
Cosmopoliteness (X6)	1.000	.542
Extension contact (X7)	1.000	**.609**
Communication material use (X8)	1.000	**.707**
Type of house (X9)	1.000	**.709**
Land holding (X10)	1.000	**.733**
Occupation (X11)	1.000	.391
Annual Income(X12)	1.000	**.769**

The communalit*ies* are computations of the extent to which a variable is explained by the components. Communalities is the total amount of variance on original variable shares with all other variables included in the analysis. PCA assumes that total variance of the original variables can be explained via the components and uses as starting values for the Communalities 1.0. Communaliti*es* is the proportion of each variable’s variance that can be explained by the factors (e.g., the underlying latent continua). It was observed that Age (X1) has the lowest communality, which indicates that age is less well explained by the analysis than any of the other variables an (increasing the number of factors increases the communality of all the variables), the variables annual income (X12), Type of house (X9), Communication material use (X8), and Land holding (X10) and Extension contact (X7) has the highest communalities . Factor loadings for the PCA is correlation between a specific observed variable and a specific factor.

However, the factor loadings or component loadings for the PCA are larger in absolute values than the communalities, and as a result, the total variance explained is likewise larger. Factor loadings for the PCA are the correlations between a certain observed variable and a particular factor. Higher levels indicate a closer bond. Better is a higher value. The PCA defines communality as the sum of all influences on a single observed variable from all of its connected components. It is the same as R2 in multiple regressions and equals the sum of all squared factor loadings for all factors associated to the observed variable. The value ranges from zero to 1 where 1 indicates that the variable can be fully defined by the factors and has no uniqueness.

Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity; measures unrotated solution, including factor loadings, communalities, and eigenvalues and rotated solution, including rotated pattern matrix and transformation matrix. Essentially it checks to see if there is a certain redundancy between the variables that we can summarize with a few number of factors. The null hypothesis of the test is that the variables are orthogonal, i.e. not correlated.

The aforementioned table showed that all of the variables for the MSA (Measures of Sampling Adequacy) had good values, but the aggregate value was only 0.748. However, Bartlett's Test of Sphericity has a p value (sig in the table) of .001. So it was determined from the data above that we can now proceed and carry out a reliable factor analysis. However, Bartlett's test of sphericity with an p value of < .001 showed that we can move forward for PCA.

Table 6. KMO and Bartlett's Test for studying appropriateness of multivariate analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**.748**
Bartlett's Test of Sphericity	Approx. Chi-Square	884.901
	Df	78
	Sig.	.000

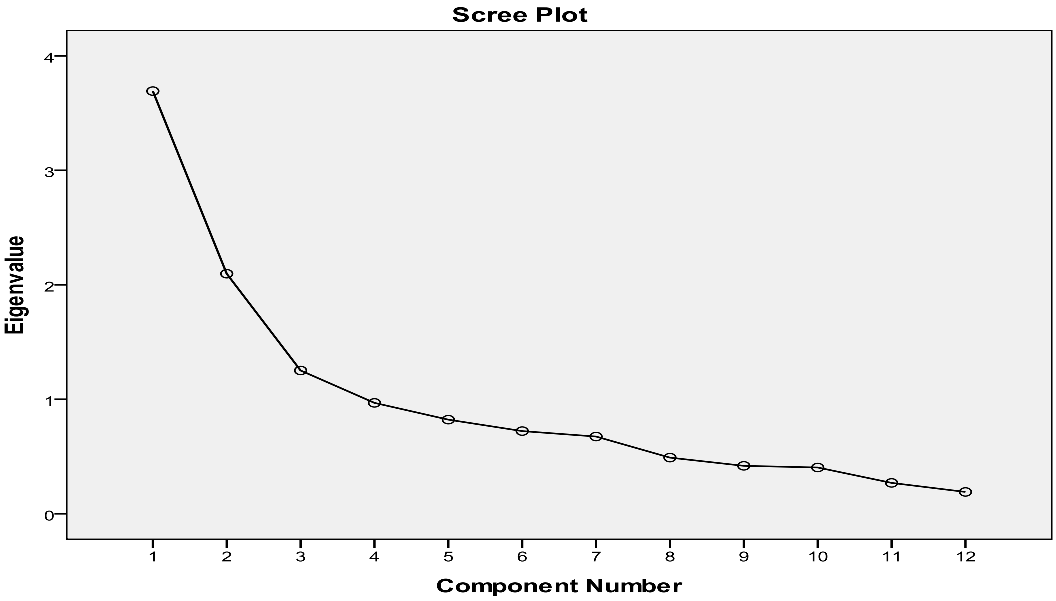

Fig. 1. Scree plot for identifying the number of components

Table 7. Rotated Component Matrix (Extraction Method)

Rotated Component Matrix			
Variables	**Component**		
	1	**2**	**3**
Land holding (X10)	.843		
Annual Income (X12)	.826		
Type of house (X9)	.822		
Cosmopoliteness (X6)	.484	.405	-.380
Education (X2)		.755	
Communication material use (X8)	.350	.733	
Social participation (X5)		.689	
Extension contact (X7)	.497	.564	
Age (X1)		.554	
Family type (X3)			.747
Family size (X4)			.680
Occupation (X11)			.621
Extraction Method: Principal Component Analysis.			
Rotation Method: Varimax with Kaiser Normalization.			

The eigenvalue is plotted against the factor number in a scree plot. It is seen that these values in the first three columns of the table immediately above. From the fourth factor onwards, we can observe that the line is almost flat, meaning the each successive factor is accounting decreasing percentage of the overall variance.

The following scree plot shows the number of Eigenvalues (λ) from the example shown on the main principal components analysis, ordered from biggest to smallest. In PCA the Kaiser criterion eliminates the components whose eigenvalues are less than 1, (when the data is standardized).

Greater than ‘1’ eigenvalue suggests that the corresponding component explains more variance than a single variable, given that a variable accounts for a unit of variance. A widely recognized criterion is called the Kaiser-Guttman rule (Kaiser, 1960) and simply states that the number of factors is equal to the number of factors with eigenvalues (λ) greater than 1.0. From the above Scree plot it was evident that only the first three components had eigenvalues (λ) greater than 1.00 and together these explained 58.66% of the total variability in the data. Thus we concluded that a three factor solution will probably be adequate.

3.2 Rotated Component Matrix (Extraction Method)

The major output of principal components analysis is the rotated component matrix, also known as the loadings.The rotated component matrix, referred to as the loadings, is the key output of principal components analysis. It contains estimates of the correlations between each of the variables and the estimated components as indicated in Table 7.The values in this column indicate the proportion of each variable's variance that can be explained by the retained factors. Variables with high values are well represented in the common factor space, while variables with low values are not well represented. They are the reproduced variances from the factors that have extracted. These values are located on the diagonal of the replication of the correlation matrix.

In the rotated factors, the variables like Land holding, Annual Income, Type of house, Extension contact and Cosmopoliteness all have high positive loadings on the first component and the variables like Education, Communication material, Social participation, Extension contact and Age have high positive loading in second component and variables like Family type, Family size and Occupation have high positive loading in third component . The eigenvalue (variance) for each principal component indicates the percentage of variation in the total data explained. Looking at the above the values more than 0.4 were highlighted, states the high loadings for each factor and that is they seem to appear logical. Only factor loadings of 0.3 or more were considered significant as earlier reported by Comrey [32] and Gorsuch [33]. To ease identification of relatively larger loadings, correlations above 0.44 are indicated in bold.

Here we have extracted three (3) principal components from the above table 7 . However the factor loadings or the component loadings for the PCA are larger in absolute values as are the communalities and as a consequence the total variance explained is also greater. Factor loadings for the PCA is equal to correlation between a specific observed variable and a specific factor. Higher values mean a closer relationship. The PCs were ranked according to the original variance they explained ie PC1 will explain the most important component and,PC2 the second most and so on.

The Kaiser Rule is the most popular method for determining the number of components, and most systems use it by default. As the total number (12) of variables were considered for the factor analysis and according to Kaiser's [34] criterion was followed to retain only those factors with Eigen values (λ) > 1.00, hence a total of three factors all having Eigen values >1.00 have been reported in the above Table. The more variables that load onto a particular component (i.e., have a high correlation with the component), the more important the factor is in summarizing the data. An eigenvalue (λ) is an index that indicates how good a component is as a summary of the data.

In PCA simply selecting the Eigen values (λ) greater than 1 is considered as Principal component and in this study, only the first three components have eigen values over 1.00 and together these explained over 58.66% of the total variability in the data. The first component (comp 1) could be explained by five socio economical variables, viz. Land holding, Annual Income, Type of house, degree of cosmopoliteness and extension contact as indicated in table 7, by the communality values (h2) of 0.843, 0.826, 0.822, 0.484 and 0,497 respectively . It was considered that farmers with higher income levels and larger land holdings make an effort to stay current with modern agricultural technical advancements and persistently seek out scientific understanding of improved watershed practises for enhancing their farm income.Farmers who own more land are considerably better equipped to accurately diagnose farming-related issues and identify creative strategies to address them. A strong scientific approach promotes systematic thinking and efficient decision-making as reported by [35]. The most variance (23.44%) in the overall variability of the data was contributed by this element, which was referred to as "resource richness." In this context, it was important to note that there are several extension agencies, both governmental and private, to meet the informational and input needs of farmers. However, those farmers who have the particular quality of cosmopoliteness tend to benefit the most from these agencies. Studies have shown that cosmopoliteness strongly correlates with the effectiveness of extensions use by [36]. The first component (comp1), which explains 23.44% of variance, is positively correlated with Land holding, Annual Income, Type of house, Cosmo politeness and extension contact. Thus, we can say (comp-1) represents resourcefulness with high extension contact and it implies that households with relatively large farm sizes are more likely higher farm income, more cosmopolite in nature due to contact with developmental agencies, acquires more knowledge about the project that leads active involvement in different watershed activities

The second component (comp 2) comprised five variables, namely Education (0.755), Communication material use (0 .733), Social participation (0.689), Extension contact (0.564.) and age (0.554) communality values (h2) respectively . The variables as mentioned clubbed together, clearly depicting that they have high degree of inter-correlation to determine knowledge level of farmers. Education, social involvement, contact with extension agents, and the use of communication tools are all crucial factors that help farmers accept more scientific knowledge through obtaining data about their farms. A knowledgeable farmer has easy access to information on the benefits of farming technology and how to use it well. The second-highest variance (20.12%) in the overall data variability was given by the element known as "education and extension contact." The second component (comp2) explains about 20. 12% of the variance and is positively correlated with education, communication materials use, social participation extension contact and age of the farmers. Thus, (comp 2) represents the young, educated experienced and innovative and progressive farmers. Age of the farmer is an influencing and important factor in the pursuit of state of economic motivation with risk motivation and it pursuits towards high economic motivation by higher adoption of improved farm technologies.

The third component (comp 3) comprised three variables namely Family type (0.747), Family size (0.680) and occupation (0.621) as communality values. Family type and family size and farming as primary occupation are found to be more important attributes that lead to success of a farmer to engage in farming for higher income by adopting new technologies in more scientific manner by gathering farm related new innovation . The factor termed as “farm family occupation” and it contributed the third highest (15.10%) variance in total data variability.

From the above Table 8, it was revealed that, Component 1 contributes 23.44% variance in knowledge level and Component 2 contributes 20. 12% variances and Component 3 contributes only 15.10% of variances in dependent variable, the knowledge level of the respondents under study. Total variance explained in this case was 58.66%, this indicates the amount of the variability in the data has been modelled by the extracted factors. It was concluded that the PCA analysis models contributed to 58.66% of the variability in this study. Component 3 (comp3) represents 15.1% of the variance and correlates positively with Family type, Family size and Occupation of the respondents. The component thus implies that big families with farming as main occupation and more number of available family workforce seeks more knowledge. It was due to the fact that, bigger the household size or joint family type and number of farm workers will be more and farming will be the primary occupation. Good socio- economic status (SES) acts as supplementary factor to influence state of motivation regarding higher income and the farmers were unevenly distributed among various socio-economic status groups. It means that they have been differing in their perception and knowledge about developmental activities in watershed areas.

Clearly the component 1 of the initial solution is much more important than the second component. However, in the right hand part of the table, the eigen values (λ) and percentage of variance explained for the three rotated factors are depicted. Whilst, taken together, the three rotated components explain just the same amount of variance (58.66%) as the three components of the initial solution, the division of importance between the three rotated factors is very important. The effect of rotation is to spread the importance more or less equally between the three rotated factors. It was noted that in the above table the eigen values (λ) of the initial solutions of component are 3.692 and 2.097 and 1.251 compared to eigen values (λ) 2.814 and 2.4145 and 1.812 in the rotated factors, this makes it clear how important it is that to extract an appropriate number of factors.

Table 8. **Extraction Method: Total Variance Explained by Principal Component Analysis**

Component	Initial Eigenvalues (λ)			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulative%**	**Total**	**% of Variance**	**Cumulative%**	**Total**	**% of Variance**	**Cumulative %**
1	**3.692**	30.767	30.767	3.692	30.767	30.767	2.814	23.446	**23.446**
2	2.097	17.473	48.240	2.097	17.473	48.240	2.415	20.122	**43.568**
3	1.251	10.429	58.669	1.251	10.429	58.669	1.812	15.101	**58.669**
4	.968	8.071	66.740						
5	.822	6.850	73.590						
6	.722	6.017	79.607						
7	.674	5.620	85.226						
8	.490	4.085	89.312						
9	.419	3.488	92.800						
10	.404	3.367	96.166						
11	.270	2.246	98.412						
12	.191	1.588	100.000						

Table 9. Component Transformation Matrix (Rotation Method: Varimax with Kaiser Normalization)

Component	1	2	3
1	.773	.634	.027
2	.352	-.464	.813
3	-.528	.619	.582

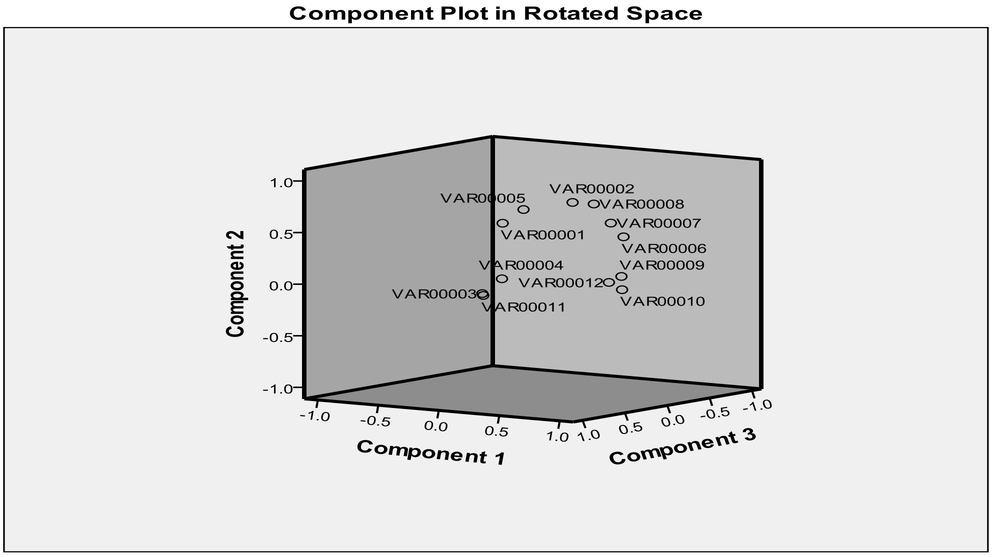

Fig. 2. Component Plot in Rotated Space
Component plot in rotated space for three PCA components

The above Table 9, gives information about the extent to which the factors have been rotated. In this case, the factors have been rotated through 45 degrees. (The angle has been calculated by treating the correlation coefficient as a cosine. The cosine of 45 degrees is 0.77).

Rotations are carried out in order to interpret the extracted factors from a factor analysis (or the components from a PCA), The components of the space-rotated graph enable a clearer presentation in which both the placement of the data in reference to the axes and the interaction between the data reveal the similarities of environmental data [37]. PCA is a powerful technique that looks to identify a new set of variables as linear combinations of the measured variables in order to decrease the number of causal factors required to explain the observed variations in the system. Together, these new variables (PCs), which are orthogonal and uncorrelated, account for all of the variation in the data. The percentage of explained variation decreases from the first principal component to the second and so forth. The majority of the information in the data was explained by a plot of the first two or three principal components because these components account for the majority of the variance, many variables can be summarised by a few components, and a plot of the first two or three PCs makes it possible to visualise the majority of the information in the data.

4. CONCLUSION

The study found that although the respondents had some knowledge of the Watershed Development Program's implementation, they lacked knowledge about a number of critical issues, including adequate funding for developmental activities, community organisation training, an emphasis on indigenous knowledge, an adequate programme for each family, participatory evaluation of progress, documentation of each activity, freedom for individuals to choose how their funds are used, and timeliness. Since the watershed development programme relies on bottom-up planning and a participatory approach, it is imperative that the beneficiaries have a thorough understanding of the operational process.

First, three components were found by principal component analysis, which was used to reduce the data to just over 58.66 percent of its total variability. According to the study's findings, three main factors—"resource richness," "education and extension contact," and "farm family and farming occupation"—were discovered to have significantly high influence and contributed 23.44%, 20.12%, and 15.1% variance in determining the extent of farmers' knowledge level about watershed activities. It was concluded that multivariate analysis (principal component analysis) are useful tools for identifying important socioeconomic characteristics of the farmers that influence their clear understanding and compliance with guidelines and technologies, as well as their full participation in the adoption of various watershed practices. The findings led to the conclusion that the project's officials must better expose the watershed's residents to the program's operating processes in order for them to fully comprehend them and ensure the project's overall development.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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