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Factors Influencing Farmers Purchase Intention toward Insecticides of Rajkot District, India

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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

The present study was conducted to identify the factors influencing farmers purchase intention toward insecticide of Rajkot district. A multi-stage random sampling method was used to select the samples during the actual survey. Total 120 insecticide users were selected randomly from Rajkot district. Principal component analysis was used to identify the factors influencing farmers purchase intention towards insecticide of Rajkot district. The result revealed that six components were product performance, financial support, product specifications, sales team influence, feedback and social influence, significantly impact farmers' purchase intentions for insecticides. The study concludes that multiple factors, including Product performance and farmer experience are the most influential, indicating the importance of reliable and effective products.

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Keywords: Insecticides; purchase intention; principal component analysis (PCA).

1. INTRODUCTION

"Agrochemicals are broadly classified as insecticides, herbicides, fungicides, rodenticides, organic pesticides and nematicides depending on the type of pest they control. Indian Agrochemical industry has approximately 125 technical grade manufacturers, 800 registered formulator, more than 1,45,000 distributors and 60 technical grades pesticides" [1]. "Insecticides are utilized by consumers, industry, and the medical field. It is said that a significant contributing cause to the rise in agricultural output in the 20th century was the use of insecticides. Insecticides can be classified into two major groups: systemic insecticides, which travel though the plant after uptake; and contact insecticides, which do not. The mode of action describes how the pesticide kills or inactivates a pest" [2]. Global Insecticides Market size was valued at USD 8.72 billion in 2019 and is poised to grow from USD 9.12 billion in 2023 to USD 13.08 billion by 2031, growing at a CAGR of 4.6% in the forecast period (2024-2031) [3]. In 2023, Maharashtra led with the highest usage, followed by Andhra Pradesh and Punjab, reflecting their extensive farming activities. States like Uttar Pradesh and Tamil Nadu also reported substantial insecticide consumption [4].

A study on the factors influencing insecticide purchase intention in Rajkot district is essential due to the region's heavy reliance on agriculture and the need for effective pest control to protect crops. Therefore, this research intended to study in-depth on this area based on Rajkot. Agrochemical business to help local retailers understand about the impact of internal and external factors on purchase intention of farmers in Rajkot. Hence this study investigates the influence of key determinants of purchase intention of farmers towards insecticide in Rajkot district. Additionally, insights from the study can guide government policies and support programs, ultimately contributing to better agricultural outcomes and economic growth in the region.

2. METHODOLOGY

2.1 Data Source

The data used in this study were obtained from survey questionnaires and interviews among farmers in Rajkot district of Gujarat. A multi-stage random sampling method was used to select the samples during the actual survey. In the first stage of sampling, the Rajkot district was selected. In the second stage, Rajkot and Paddhari two talukas were selected purposely for the same reason. In the third stage, four villages from each talukas were selected randomly, and from each villages, fifteen insecticide users were selected randomly. Hence, a total of 120 insecticide users were selected for the study from Rajkot district in the year 2024. Data about farmers using insecticides was gathered directly from farmers.

2.2 Statistical Method

Principal component analysis was used to find out factors influencing the purchase intention of insecticide. Under the factor model assuming linearity, each response variate is represented as a linear function of small number of unobservable common factor and a single latent specific factor. The common factor generates covariance among observable response while a specific term contributes only to the variance of particular term. The co-variation among the variables is described in terms of a small numbers of common factors, plus a unique factor for each variable. These factors are not over observed. If the variables are standardized, the factor model may be represented as: [5].

$$\boldsymbol{X_i = A_{i1}F_1 + A_{i2}F_2 + A_{i3}F_3 + \dots\dots + A_{im} + F_m + V_iU_i}$$

Where,

X_i= i^{th} Standardized variable
A_{ij}= Standardized multiple regression coefficient of variable i on common factor j
F= Common factor
V_i= Standardized regression coefficient of variable i on unique factor i
U_i= Unique factor for variable i
m= Number of common factors

There is no correlation between the common factor and the unique factors. The common factor themselves can be expressed as linear combination of observed variable.

The unique factor model is expressed as below:

$$\boldsymbol{Fi = Wi1X1 + Wi2X2 + Wi3X3 + \dots\dots + WikXk}$$

Where,

Fi= Estimate of ith factor
Wi= Weight or factor score coefficient
K= Number of variables [6].
X1= Name of product (Easy / Moderate / Difficult)
X2= Cost per pump (High / Medium / Low)
X3= Quality of product (Good / Average / Poor)
X4= Rate of effectiveness (Highly Satisfactory /Satisfactory /Need Improvement)
X5= Own experience of farmer (Good / Average / Poor)
X6= Result of product (Good / Average / Poor)
X7= Types of packaging (Good / Average / Poor)
X8= Availability of product (Regular / Irregular))
X9= Affordability of product (Affordable / Not affordable)
X10= Availability of credit facility (Yes / No)
X11= Attractive schemes and discount to farmer (Yes / No)
X12= Influence by friends and other farmers (Yes / No)
X13 = Influence by sales officer (Yes / No)
X14 = Influence by retailer (Yes / No)
X15 =Influence by field assistant (Yes / No)
X16 = Promotional activities (Yes / No)
X17 = Feedback activities (Yes / No)

To ensure that the first component accounts for the majority of the overall variation, weights or factor score coefficients might be chosen. Then, a second set of weight can be selected, so that the second factor accounts for most of the residual variance, subject to being uncorrelated with the first factor. We might use the same idea to choose additional weights for the extra elements. Thus, the factors can be estimated so that the scores of their factors, unlike the value of the original variable, are not correlated. Furthermore, the first factor accounts for the highest variable in the data, the second factor the second highest, and so on [7].

3. RESULTS AND DISCUSSION

Principal component analysis was used to find out the factors influencing purchase intention of insecticide among farmers. A statistical technique called principal component analysis is used to express the variability between associated, observable variables in terms of a smaller number of possible unobserved variables known as factors. In response to latent variables that are not observed, principal component analysis looks for such joint variations.

3.1 KMO and Bartlett's Test

Based on the Table 1. it was interpreted as followed.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO): The KMO value in this case was 0.682, which exceeded the minimum threshold of 0.50 [8] and 0.60 [9]. It indicated a sufficient degree of correlation among the variables, suggesting that the data was suitable for principal component analysis. The value of 0.682 suggested that the sample size was adequate for conducting the principal component analysis.

Bartlett's Test of Sphericity: Bartlett's Test of Sphericity was used to test the null hypothesis that the individual indicators in a correlation matrix were uncorrelated (i.e., the correlation matrix was an identity matrix). A p-value less than 0.05 indicated that a principal component analysis was effectively applied to the data set. However, it was important to consider that Bartlett's test was highly sensitive to sample size. Hence, researchers recommended implementing it together with the KMO measure.

In this case, the test statistic was approximately 1795.595 with 136 degrees of freedom. The p-value was very small (0.000), indicated that the correlation matrix was not an identity matrix, further supporting the suitability of the data for principal component analysis. Principal component analysis was used to find out the factors influencing purchase intention of insecticides.

Principal component analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. Principal component analysis searches for such joint variations in response to unobserved latent variables.

Table 1. KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.682
Bartlett's Test of Sphericity	Approx. Chi-Square	1795.595
	Df	136
	Sig.	.000

Table 2. Total Variance explained

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.753	22.077	22.077	3.589	21.112	21.112
2	2.940	17.295	39.372	2.848	16.754	37.866
3	2.784	16.379	55.751	2.830	16.645	54.511
4	2.010	11.824	67.575	1.807	10.627	65.139
5	1.750	10.296	77.871	1.772	10.426	75.565
6	1.350	7.943	85.814	1.742	10.249	85.814
7	.772	4.543	90.357			
8	.379	2.227	92.584			
9	.288	1.694	94.278			
10	.261	1.536	95.814			
11	.192	1.130	96.945			
12	.154	.907	97.852			
13	.116	.683	98.535			
14	.095	.558	99.093			
15	.075	.439	99.532			
16	.049	.289	99.821			
17	.030	.179	100.000			

3.2 Total Variance Explained

The Table 2, showed the initial eigen values and the rotated sums of squared loadings for each component. The components were numbered from 1 to 17. The Kaiser's rule, was based on the size of variances of principal components; the idea was to retain only those principal components whose variances exceeded 1 [10]. Accordingly, the extraction of PCs was based on components with eigen values greater than 1. Based on this rule, it was clear from Table 2 that the first six components had their eigenvalues over 1 and were large enough to be retained. The first component had the highest eigen value (3.753), accounting for most of the variation in the data sets (22.077 per cent). After rotation, this component's eigenvalue was 3.589, explaining 21.112 per cent of the variance. The second component had an initial eigenvalue of 2.940, accounting for 17.295 per cent of the variance, and after rotation, its eigenvalue increased to 2.848, accounting for 16.754 per cent of the variance. The third component had an initial eigenvalue of 2.784, accounting for 16.379 per cent of the total variance, and a rotated eigenvalue of 2.830, accounting for 16.645 per cent of the variance. The fourth component had an initial eigenvalue of 2.010, accounting for 11.824 per cent of the total variance, and a rotated eigenvalue of 1.807, explaining 10.627 per cent of the variance. The fifth component's initial eigenvalue was 1.750, accounting for 10.296 per cent of the total variance, with a rotated eigenvalue of 1.772, accounting for 10.426 per cent of the variance. The sixth component had an initial eigenvalue of 1.350, accounting for 7.943 per cent of the total variance, and a rotated eigenvalue of 1.742, explaining 10.249 per cent of the variance. These six components explained a cumulative variance of 85.814 per cent in the data.

This analysis indicates that the 17 original variables related to the factors influencing purchase intention of insecticide were effectively reduced to seven underlying factors. These six components together explained 85.814 per cent of the variance in the data, suggesting a multidimensional construct underlying farmers' factors influencing purchase intention of insecticide.

3.3 Factor Extraction with the Scree Plot

The factor extraction with the scree plot, which showed decreasing eigen values on the y-axis and the relevant number of components on the x-axis. The Kaiser rule of eigen values greater than 1 was used as a supplementary objective criterion or "stopping rule" for retaining components [11,12]. As shown in Fig. 1., using this rule, point y = 1 on the graph represented the Kaiser criterion cut-off point, according to which six components satisfied this rule and were retained; the other factors starting from the eighth were thereby ignored and were subsequently excluded from the model.

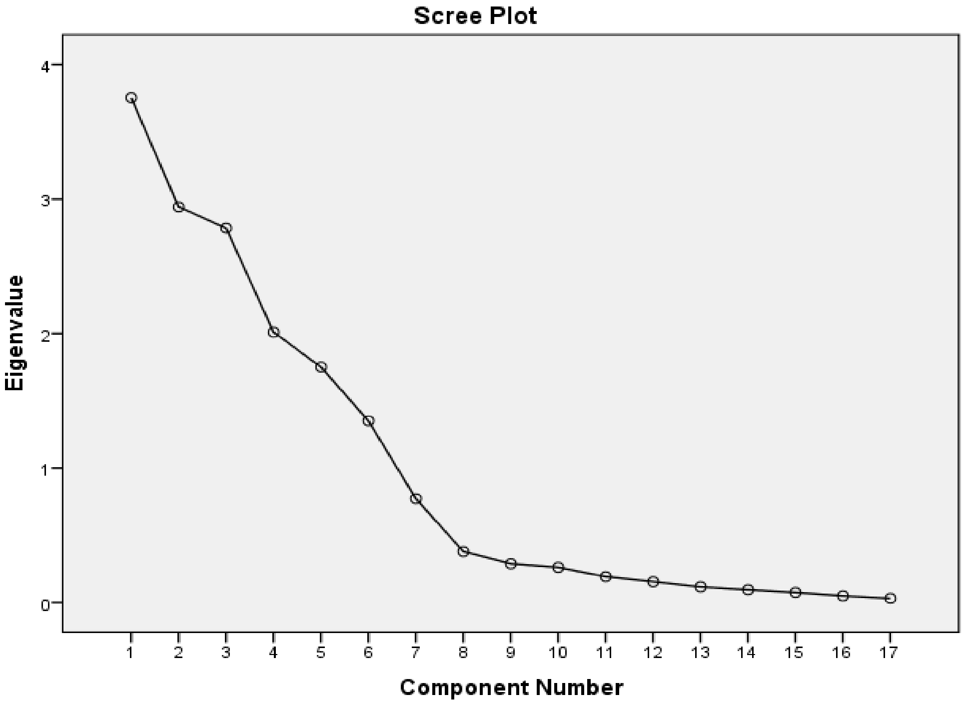

Fig. 1. Scree plot for eigen values

Table 3. Rotated component matrix

Rotated Component Matrix[a]						
	Component					
	1	**2**	**3**	**4**	**5**	**6**
Result of product	**.979**	.019	-.043	.013	.033	-.002
Rate of effectiveness	**.953**	-.015	-.059	.054	-.002	-.025
Quality of product	**.930**	-.019	-.056	.019	.032	-.053
Own experience of farmer	**.909**	.015	-.006	.005	.048	.073
Availability of credit facility	-.016	**.963**	-.001	-.012	.104	-.005
Affordability of product	-.009	**.958**	-.026	.009	.081	.006
Attractive schemes and discount to farmer	.018	**.948**	.083	-.022	.031	.037
Types of packaging	-.062	.008	**.981**	-.029	-.066	.023
Cost per pump	-.049	.034	**.955**	-.013	.028	.017
Name of product	-.036	.010	**.951**	.008	-.070	.087
Influence by sales officer	.037	.054	.029	**.921**	.027	.099
Influence by field assistant	.025	-.087	-.053	**.918**	.088	.061
Feedback activities	.037	.154	-.024	.084	**.895**	-.031
Promotional activities	.071	.065	-.085	.047	**.876**	-.135
Influence by retailer	-.017	.039	-.014	.114	-.081	**.849**
Influence by friends and other farmers	.075	.111	.072	.173	-.229	**.834**
Availability of product	-.091	-.223	.129	-.241	.324	**.525**

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaiser Normalization
[a.] *Rotation converged in 6 iterations*

3.4 Rotation of the Components

The Table 3, presented the rotated component matrix. A rotation was a linear transformation that was performed on the initial factor solution for the purpose of making an easier interpretation [13]. Various approaches for the rotation of the components had been proposed. The most common rotation method was orthogonal varimax [14,15], which was applied in the current study obtained 6 components from 17 variables; Only the variables with a factor loading greater than 0.50 were included as factors following the recommendations of [16], variables with factor loadings below 0.5 were eliminated.

3.5 Labelling of the Components

Each of the six components included in Table 4. were labelled with an appropriate name according to the components that loaded most highly for that dimension (see Table 4).

The study underscores that farmers' insecticide purchasing decisions are heavily driven by the product's performance and their personal experiences. Effectiveness, quality, and the results achieved by the insecticide are critical factors, as they directly impact the farmers' satisfaction and likelihood of repeat purchases. Positive personal experiences with a product enhance its perceived value, making it a preferred choice among farmers. These insights suggest that manufacturers should focus on delivering high-quality, effective products and ensure that they meet farmers' expectations to foster loyalty and drive sales.

In addition to product performance, financial considerations and market dynamics significantly influence purchasing decisions. Factors such as the affordability of the product, the availability of credit, and promotional discounts are crucial in determining whether farmers can afford and choose to purchase the insecticide. Product specifications, including packaging and cost per unit, also affect decisions, alongside the role of sales staff and market availability. Addressing these aspects effectively can help manufacturers tailor their strategies to better align with farmers' needs, thereby improving market penetration and customer satisfaction.

Table 4. Labelling of the component

Sr. No.	Factors
Component:1 Product performance and farmer experience	
06	Result of product
04	Rate of effectiveness
03	Quality of product
05	Own experience of farmer
Component:2 Financial support	
10	Availability of credit facility
09	Affordability of product
11	Attractive schemes and discount to farmer
Component:3 Product specification	
07	Types of packaging
02	Cost per pump
01	Name of product
Component:4 Sales team influence	
13	Influence by sales officer
15	Influence by field assistant
Componenent:5 Feedback and promotional activities	
17	Feedback activities
16	Promotional activities
Component:6 Market influence and product availability	
14	Influence by retailer
12	Influence by friends and other farmers
08	Availability of product

4. CONCLUSION

The study concludes that multiple factors, including product performance, financial support, product specifications, sales team influence, feedback, and social influence, significantly impact farmers' purchase intentions for insecticides in Rajkot district. Product performance and farmer experience are the most influential, indicating the importance of reliable and effective products. Financial support and attractive schemes also play a crucial role in purchase decisions. Based on these findings, it is recommended that manufacturers focus on improving product quality and effectiveness, offer flexible financial options, and enhance the role of sales teams in providing tailored advice. Additionally, leveraging feedback and strengthening relationships with retailers and local influencers can further boost market penetration.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that generative AI technologies such as Large Language Models, etc have been used during writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology.

Details of the AI usage are given below:

1. ChatGPT has been used while editing conclusion, abstract and R& D. once the text has been written by author then to improve language and editing purpose ChatGPT has been used.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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