Discriminant analysis of plant growth regulators among vegetable growers in Junagadh district of Gujarat

ABSTRACT

In an agrarian economy like ours, agriculture productivity is of vital importance for farmers' economic wellbeing and national prosperity. The differential adoption of PGRs among vegetable growers can offer insights into broader agricultural practices. Understanding PGR use in vegetable provides a comparative basis for evaluating its impact on diverse crops in the region. This study examines the socio-economic profile and identifies distinguishing factors between users and non-users using a sample of 160 farmers (80 users and 80 non-users) in Junagadh district, Gujarat. Analyses included simple tabular analysis and discriminant analysis. In this study, it was observed that most farmers were aged 36 to 50 years, and all respondents were male. The majority had an education level of 1st to 8th standard and an income up to 2 lakhs. Most farmers had landholdings of 2.01 to 4.00 hectares, engaged in both agriculture and animal husbandry, and had over 12 years of farming experience. Linear discriminant analysis identified annual family income, education, quality of yield and awareness as the most significant variables in distinguishing between users and non-users of plant growth regulators.

Keywords: *Plant growth regulators, vegetable, socio-economic profile, simple tabular analysis, discriminant analysis*

1. INTRODUCTION

Vegetables are an essential component of human diets, offering a rich source of vitamins, minerals, fiber, and phytonutrients. They are classified based on the part of the plant consumed, such as roots (carrots, beets), stems (celery, asparagus), leaves (spinach, lettuce), flowers (broccoli, cauliflower), fruits (tomatoes, cucumbers), and seeds (peas, beans). The diverse nutritional profiles of vegetables contribute to their role in promoting health and preventing diseases, including heart disease, obesity, and certain types of cancer. Furthermore, the variety of colors, textures, and flavors found in vegetables enhances culinary diversity and supports sustainable food systems by promoting local and seasonal eating. (Slavin and Lloyd, 2012 [1]; Bazzano, 2006 [2]).

In addition to increasing productivity, using phytohormones and micronutrients will boost vegetable crop yield and fertilizer usage efficiency (Kumar *et al.* 2007) [3]. Plant growth regulators are vital components of plants that have a variety of effects on their physiology. They are essential to the development of foliage, flowers, fruits, and other quality products, as well as to both vegetative and reproductive growth. Discriminant analysis is a statistical technique designed to investigate the difference between two or more groups of cases with respect to several underlying variables. This technique is more appropriate than commonly used measures (i.e., correlations and regressions) when the variables being predicted are categorical. Its goal is to explain and predict the group membership of items based on measurements of explanatory variables (Rede and Bhattacharyya 2021) [4].

Discriminant analysis can effectively distinguish between different groups based on their characteristics. In the context of this study, it can be utilized to identify the distinguishing factors between Plant Growth Regulator (PGR) among vegetable growers in the Junagadh District of Gujarat. By examining variables such as socio-economic status, farm size, education level, and access to agricultural extension services, discriminant analysis can offer a nuanced understanding of the profiles of these two groups. This technique has been widely used in agricultural research to analyze differences in farmer behavior and technology adoption (Hair *et al.* 2010[5]; Morrison, 1969[6]).

The significance of this research lies in its potential to inform policy and extension services aimed at improving vegetable production. By identifying the key determinants of PGR usage, strategies can be developed to encourage the adoption of these beneficial practices, thereby enhancing productivity and sustainability in vegetable cultivation. Previous studies have highlighted the importance of such analyses in other agricultural contexts, demonstrating the relevance and applicability of this approach (Singh *et al.* 2019[7]; Sharma and Chauhan, 2020[8]).

2 METHODOLOGY

2.1 Sampling design

The current experiment employed a multistage sampling approach to select the final sample unit. In the first stage, Junagadh district of Gujarat was chosen purposefully due to the company's intent to establish a market presence in the area. This district was selected for its significance in examining the socio-economic profiles of farmers and the factors discriminating users and non-users of plant growth regulators. In the second stage, the talukas of Junagadh and Vanthali within the district were specifically chosen, aligning with the company's strategy to focus market development efforts in these areas. In the third stage, a total of 8 villages from Junagadh taluka and 8 villages from Vanthali taluka were randomly selected to provide a broad representation of the areas within each taluka. In the final stage, 10 farmers were randomly chosen from each selected village, comprising 5 users and 5 non-users of plant growth regulators. This resulted in a total of 80 farmers from Junagadh taluka (40 users and 40 non-users) and 80 farmers from Vanthali taluka (40 users and 40 non-users), creating a comprehensive sample of 160 farmers across the district.

2.1 Analytical tools

2.1.1 Simple tabular analysis

Simple tabular analysis and graphical presentations were used to examine the socio-economic profile of farmers.

2.1.2 Linear Discriminant Analysis

Linear discriminant analysis was used to identify the determinants of plant growth regulator users and non-users. Discriminant function analysis (DFA) is a parametric technique used to identify the weightings of quantitative variables or predictors that best differentiate between two or more groups of cases, outperforming random chance. This analysis generates a discriminant function, which is a linear combination of the weightings and scores of these variables. The maximum number of discriminant functions created is the lesser of either the number of predictors or the number of groups minus one.

$$Z_{jk} = a + W_1X_{1k} + W_2X_{2k} + ... + W_nX_{nk}$$

Where,

Z_{jk} = The Z score of discriminant function j for object k
a = Intercept.
W_i = Discriminant coefficient for the independent variable *i.*
X_j = Independent variable *i* for object *k.*

Again, it is important to emphasize that the aim of the analysis is sometimes to explain relationships rather than to predict outcomes. In these cases, equations are typically not used, especially when the measures involved are not objective (Ramayah *et al.* 2010) [9].

The discriminant function of the following form was used:

$$\mathbf{Z = L_1 X_1 + L_2 X_2 + L_3 X_3 + L_4 X_4 + L_5 X_5 + L_6 X_6 + L_7 X_7 + L_8X_8 + L_9X_9}$$

Where,

Z = Composite discriminant scores for the two groups.
Xi's = Variables selected to discriminate the groups. Li's = Discriminant coefficients.
SI = D

$$S = \begin{matrix} S_{11} & S_{12} \ldots\ldots S_{1k} \\ S_{21} & S_{22} \ldots\ldots S_{2k} \\ : & : \quad\quad : \\ S_{k1} & S_{k2} \ldots\ldots S_{kk} \end{matrix} \qquad I = \begin{matrix} L_1 \\ L_2 \\ : \\ L_k \end{matrix} \qquad \text{and } D = \begin{matrix} d_1 \\ d_2 \\ : \\ d_k \end{matrix}$$

Where,

K = Number of variables
L_k = Vector of coefficient of discriminant function
S = Pooled dispersion matrix, and
D = Vector of difference between the mean value of different characteristics for the two groups.

Discriminant function was tested for significance to examine whether the variables considered together were sufficiently discriminating between the groups of plant growth regulator users and non-users of plant growth regulators. The Mahalanobis D^2 test was used to measure the distance between the two groups. After transformation of the D^2 statistics, it becomes an F statistic, which was then used to see the group difference from each other. For this, Statistic 'F' was computed as under

$$F = \frac{N_a N_B \left(N_a N_b - P - 1\right)}{P\left(N_a N_b\right)\left(N_a N_b - 2\right)} \times D^2$$

P is the number of variables considered in the function. The value of 'F' was tested for its significance at (P) and (Na +Nb – P – 1) degrees of freedom (Divya *et al*. 2014) [10].

3. RESULTS AND DISCUSSION

3.1 Socio-economics profile of the farmers

The socio-economic status of farmers refers to the social and economic conditions in which farmers live and operate. The data presented in Table 1 illustrated the distribution of users and non-users across different variables. The majority of farmers were in the middle age group (36-50 years), comprising 56.25 per cent of the sample, while older farmers (above 50 years) accounted for 40.62 per cent. All respondents were male, indicating that the farming community was male-dominated. Most farmers had completed primary education (46.25%), while 28.12 per cent were illiterate. A smaller number had attained secondary or higher education. Half of the farmers had low income (up to 2 lakhs), with 28.12 per cent in the medium income range (2-4 lakhs) and 21.88 per cent in the high-income category (above 4 lakhs). Medium-sized land holdings (2.01 to 4.00 ha) were most common, accounting for 48.75 per cent of farmers. Smaller and marginal holdings were less prevalent. A significant portion (71.87%) of farmers were engaged in both agriculture and animal husbandry, while 16.87 per cent focused solely on agriculture. The majority of farmers (57.50%) had over 12 years of farming experience, with smaller groups having 1-5 years (11.87%) and 6-12 years (30.62%) of experience.

Table 1 Socio-economic profile farmers (n=160)

Description of variables	**Frequency**			**Per cent**
	User	**Non-User**	**Total**	
Age group				
Young (less than 35 years)	3	2	5	3.13
Middle (between 36 to 50 years)	52	38	90	56.25
Old (above 50 years)	25	40	65	40.62
Gender of farmers				
Male	80	80	160	100
Female	0	0	0	0
Education of farmers				
Illiterate	15	30	45	28.12

Primary (1st to 8th standard)	35	39	74	46.25
Secondary (9th to 10th standard)	20	8	28	17.50
Higher secondary (11th to 12th standard)	6	3	9	5.63
Graduate	3	0	3	1.87
Post Graduate	1	0	1	0.62
Annual income of farmers				
Low income (Up to 2 lakhs)	20	60	80	50.00
Medium income (2-4 lakhs)	30	15	45	28.12
High income (above 4 lakhs)	30	5	35	21.88
Land holdings of farmers				
Marginal size (up to 1.00 ha.)	2	4	6	3.75
Small size (1.01 to 2.00 ha.)	10	21	31	19.38
Medium size (2.01 to 4.00 ha.)	43	35	78	48.75
Large size (more than 4.00 ha.)	25	20	45	28.12
Occupation wise distribution of farmers				
Agriculture	15	12	27	16.87
Agriculture + Animal husbandry	57	58	115	71.87
Agriculture + Other	8	10	18	11.25
Farming experience of farmers				
1 - 5 years	4	15	19	11.87
6 - 12 years	16	33	49	30.62
Above 12 years	60	32	92	57.50

(Source: Field survey, 2024)

3.2 Discriminant analysis

The discriminant function analysis was carried out in order to examine the relative importance of different factors discriminating users and non-users of plant growth regulator. The coefficients of the discriminant function measure the net effect of an individual variable when all other variables were taken as constant.

Table 2 Summary of canonical discriminant function

Eigen values				
Function	**Eigenvalue**	**% of Variance**	**Cumulative %**	**Canonical Correlation**
1	9.022	100.0	100.0	.949

An Eigen value (9.022) indicates the proportion of variance explained. This Eigen value was related to the canonical correlations and describe how much discriminating ability a function possesses.

The canonical relation refers to the correlation between discriminant scores and the levels of the dependent variable. This correlation (0.949) indicates a function discriminates well between users and non-users of plant growth regulator.

Wilks' Lambda is the ratio of within groups sums of squares to the total sums of squares. This represents the fraction of the overall variability in discriminant scores that remains unaccounted for by group differences. Here, the Lambda of 0.100 has a significant value (Sig. = <0.001), thus, the group means appear to differ which indicates that the model significantly differentiates scores among the groups.

Table 3 Wilks' Lambda significance test

Test of Function(s)	**Wilks' Lambda**	**Chi-square**	**df**	**Sig.**
1	.100	353.786	9	.000

The Wilk's Lambda, the F-values and their level of significance for each variable are presented in Table 4 the coefficients of different set of variables analyzed separately and their effect in determining the discrimination among two groups were subjected for level of significant. The wilk's lambda in the result showed that the ratio of within groups sum of squares to the total sum of squares. The value of wilk's lambda lies from zero to one if the value is nearest to zero indicates strong group differences or the data from each group are different and if the value nearest to one indicates no group differences or the data from each group are similar and vice-versa. The results indicated that variables such as annual family income, education, land holding, availability, cost, peer group influence, farming experience, brand image, awareness, and quality of yield were significant at $p \leq 0.05$.

Table 4 Tests of equality of group means

Discriminant Variables	Wilks' Lambda	F	df_1	df_2	Sig.
Annual family income	.730	58.319	1	158	.000*
Education	.908	16.039	1	158	.000*
Percentage of total vegetables cultivated Land	.970	4.942	1	158	.028**
Brand Image	.872	23.229	1	158	.000*
Quality of yield	.260	448.572	1	158	.000*
Farming experience	.878	21.933	1	158	.000*
Peer group influence	.926	12.704	1	158	.000*
Availability of Plant growth regulator	.921	13.567	1	158	.000*
Awareness	.315	343.255	1	158	.000*

*** Significant at 1 % level of significance**

**** Significant at 5 % level of significance**

Results for the test of equality of group means are given in Table 4. When the value of Wilk's lambda approaches one, there is no significant difference in the means of two groups and vice-versa. It showed that the users and non-users of plant growth regulator differed widely in relation to value of above mention variables. The other test used in the process of discriminant analysis was correlation between discriminating variables and canonical discriminant function.

Table 5 Correlation between discriminating variables and the canonical discriminant function

Discriminant Variables	Standardized Canonical Discriminant Function Coefficients	Rank
Annual family income	**.779**	**1**
Education	**.756**	**2**
Percentage of total vegetables cultivated Land	.352	6
Brand Image	.113	8
Quality of yield	**.680**	**3**
Farming experience	.455	5
Peer group influence	-.031	9
Availability of Plant growth regulator	.274	7

Awareness	**.541**	**4**

The correlation coefficient was ranked according to their contribution in the discriminant function. It could be seen from the Table 5 that value of annual family income (0.779), education (0.756), quality of yield (0.680) and awareness (0.541) have highest contribution among all other variables.

Table 6 Factor contribution of individual characteristics for users and non-users of plant growth regulator

Discriminant variables	Coefficient (IK)	Mean difference (DK)	Contribution of variable (IK×DK)	Factor contribution (%)
Annual family income	**1.132**	**0.8306**	**0.94**	**15.75**
Education	**0.811**	**0.5903**	**0.48**	**8.02**
Percentage of total vegetables cultivated Land	0.449	0.2754	0.12	2.07
Brand Image	0.350	0.2466	0.09	1.45
Quality of yield	**2.672**	**0.8519**	**2.28**	**38.13**
Farming experience	0.692	0.4863	0.34	5.64
Peer group influence	-0.094	0.1842	-0.02	-0.29
Availability of Plant growth regulator	1.079	0.1481	0.16	2.68
Awareness	**1.946**	**0.8148**	**1.59**	**26.56**
Total			**5.97**	**100.00**

The discriminant function for the data was estimated as:

$$\mathbf{Z = 1.132\, X_1 + 0.811\, X_2 + 0.449\, X_3 + 0.350\, X_4 + 2.672\, X_5 + 0.692\, X_6 - 0.094\, X_7 + 1.079\, X_8 + 1.946\, X_9}$$

X_1 = Annual family income (Rs/Annum)
X_2 = Education (Years)
X_3 = Percentage of total vegetables cultivated land (ha)
X_4 = Brand Image (Good/Bad)
X_5 = Quality of yield (Improved/Not improved)
X_6 = Farming experience (Years)
X_7 = Peer group influence (Yes/No)
X_8 = Availability of Plant growth regulator (Yes/No)
X_9 = Awareness (Aware/Not-aware)

Based on the data presented in Table 6, certain variables stood out as the most influential factors in discriminating between users and non-users of plant growth regulators. These variables included annual family income, education, quality of yield and awareness. In contrast, variables such as percentage of total vegetables cultivated land, brand image, farming experience, peer group influence, and availability of plant growth regulators contributed the least in distinguishing between the two groups. Table 6 showed that the contribution of these factors was very negligible.

Annual family income, education, quality of yield, and awareness were the most contributing variables in discriminating between the groups, with factor contribution percentages of 15.75 per cent, 8.02 per cent, 38.13 per cent, and 26.56 per cent, respectively. In contrast, variables such as percentage of total vegetables cultivated land, brand image, farming experience, peer group influence, and availability of plant growth regulators showed relatively less contribution to the discrimination between users and non-users. This suggested that these factors had minimal influence on farmers' decisions regarding the use of plant growth regulators.

The discriminant analysis reveals that the primary factors influencing the use of PGRs are related to the direct benefits and awareness of these products. Quality of yield stands out as the most critical factor, suggesting that the perceived improvement in crop quality strongly motivates farmers to adopt PGRs. Awareness is crucial because it equips farmers with the knowledge needed to appreciate and effectively use these regulators.

Higher annual family income enables farmers to invest in PGRs, and better education and farming experience further empower them to understand and implement these technologies effectively. Availability of PGRs is necessary but not sufficient on its own; farmers must be informed and convinced of their benefits for availability to translate into usage.

Less significant factors include the extent of vegetable cultivation, brand image, and peer influence. These do not directly impact a farmer's knowledge or capability to utilize PGRs effectively. Peer influence, in particular, may have a negligible or even negative effect, suggesting that individual decision-making based on personal awareness and experience is more critical.

The values of mean and the mean difference in characteristics are presented in Table 7. Relatively higher mean differences were observed in case of annual family income and quality of yield.

Table 7 Different discriminant variables with mean values

Discriminant variables	Users of plant growth regulator	Non users of plant growth regulator	Total	Mean difference
Annual family income	**2.1392**	**1.3086**	**1.7188**	**0.8306**
Education	**2.4051**	**1.8148**	**2.1063**	**0.5903**
Percentage of total vegetables cultivated Land	3.1519	2.8765	3.0125	0.2754
Brand Image	.9873	.7407	.8625	0.2466
Quality of yield	**1.0000**	**.1481**	**.5688**	**0.8519**
Farming experience	2.6962	2.2099	2.4500	0.4863
Peer group influence	.9620	.7778	.8688	0.1842
Availability of Plant growth regulator	1.0000	.8519	.9250	0.1481
Awareness	**1.0000**	**.1852**	**.5875**	**0.8148**

For the relative importance of the significant characteristics of user of plant growth regulator and non-user of plant growth regulator, the function was re-estimated by taking only significant variables in the equation to see whether these characteristics alone could discriminate user of plant growth regulator and non-user of plant growth regulator groups significantly. The newly estimated discriminating function, considering only the significant factors, is as follows:

$$\mathbf{Z = 1.132\,X_1 + 0.811\,X_2 + 2.672\,X_5 + 1.946\,X_9}$$

Where,

X_1 = Annual family income (Rs/Annum)

X_2 = Education (Years)

X_5 = Quality of yield (Improved/Not improved)

X_9 = Awareness (Aware/Not-aware)

Table 8 Relative importance of significant characteristics for users and non-users of plant growth regulator

Sr. No.	Discriminant variables	Coefficient (IK)	Mean difference (DK)	Contribution of variable (IK×DK)	Factor contribution (%)
1	Annual family income (X_1)	1.132	0.8306	0.94	17.77
2	Education (X_2)	0.811	0.5903	0.48	9.07
3	Quality of yield (X_5)	2.672	0.8519	2.28	43.10
4	Awareness (X_9)	1.946	0.8148	1.59	30.06
Total				**5.29**	**100.00**

According to the results presented in Table 8, several factors contribute to discriminating between users and non-users of plant growth regulator. Annual family income, with a discriminant coefficient of 1.132 and contributing 17.77 per cent to the total factor contribution, moderately influences the likelihood of adopting PGRs. Higher family incomes provide farmers with greater financial flexibility to invest in new technologies and agricultural inputs. PGRs, while beneficial, represent an additional cost. Families with higher incomes can afford these costs without compromising other essential expenditures. This financial capability allows them to experiment with and adopt innovative solutions aimed at enhancing agricultural productivity and yield quality.

Education has a coefficient of 0.811 and contributes 9.07 per cent to the total factor contribution. Educated farmers are more likely to understand the scientific principles and practical applications of PGRs. They can better interpret and utilize information from agricultural research, extension services, and training programs. This understanding helps them make informed decisions about the adoption of new technologies. Moreover, education can enhance farmers' ability to access and evaluate different sources of information, weigh the benefits and risks, and implement PGRs effectively. Therefore, education plays a crucial role in bridging the gap between scientific knowledge and practical application in the field.

The quality of yield, with the highest coefficient of 2.672 and contributing a significant 43.10 per cent to the total factor contribution, is the most influential factor. The primary reason behind this is the direct economic impact of improved yield quality. Better quality produce often fetches higher market prices, increases competitiveness, and meets consumer demands more effectively. Farmers who perceive a substantial improvement in yield quality due to PGR usage are more inclined to adopt these regulators. Scientifically, PGRs can enhance various aspects of crop quality, such as size, color, taste, and nutritional content, making the produce more attractive to buyers and markets. This economic incentive is a powerful motivator for adoption, as farmers aim to maximize their returns on investment.

Awareness has a coefficient of 1.946 and contributes 30.06 per cent to the total factor contribution. Awareness is critical as it serves as the initial step in the adoption process. Farmers who are well-informed about the benefits, proper usage, and potential outcomes of PGRs are more likely to consider and adopt them. Awareness can be raised through various channels, including agricultural extension services, farmer training programs, media, and peer networks. The more aware farmers are of the advantages and correct application techniques of PGRs, the more likely they are to overcome any apprehensions or misconceptions. This informed decision-making process is essential for the successful integration of PGRs into regular farming practices.

The discriminant analysis highlights that quality of yield is the most influential factor in differentiating users from non-users of PGRs, followed by awareness, annual family income, and education. These findings suggest that efforts to promote PGR adoption should focus on demonstrating the yield benefits, increasing farmer awareness, and supporting educational initiatives to equip farmers with the necessary knowledge to effectively use PGRs.

From the Table 9, it was seen that the discriminant function 100.0 per cent classify the users of plant growth regulator while 98.8 per cent for non-users of plant growth regulator.

Table 9 Classification of results for the discriminant function

Category		**Plant growth regulator**	**Predicted Group Membership**		**Total**
			Non user	**User**	
Original	Count	Non user	80	1	81
		User	0	79	79
	%	Non user	**98.8**	1.2	100
		User	0	**100**	100
Cross-validated	Count	Non user	79	2	81
		User	0	79	79
	%	Non user	**97.5**	2.5	100
		User	0	**100**	100

The classification accuracy of discriminant analysis using the cross-validation with one random observation omitted at each time in the Table 9 and it was seen that accuracy remains the same i.e., 100.0 per cent for users of plant growth regulator and 98.8 per cent for non-users of plant growth regulator. The findings of this study are likely to align with previous research studies that have examined similar themes and utilized discriminant analysis techniques to classify or discriminate groups of farmers based on specific variables. According to Lwayo (2007) [11], Halagundegowda *et al.* (2017) [12] and Sinha and Dhaka (2013) [13] have found the same level of finding in their study.

While the specific variables or parameters used to discriminate or classify the groups may vary depending on the research topic of each study, this study contributes in the field of research by employing discriminant analysis techniques to understand the relationship between factors such as annual family income, education, land holding, availability, cost, peer group influence, farming experience, brand image, awareness, and quality of yield among different groups of farmers.

4. CONCLUSION

The research highlights the pivotal role of plant growth regulators (PGRs) in enhancing the productivity and quality of vegetable. The demographic analysis revealed that the majority of farmers were middle-aged males with limited formal education and moderate incomes, predominantly managing medium-sized landholdings and engaging in both agriculture and animal husbandry. Yield quality, awareness, annual family income, and education were key factors discriminating the user and non-user of plant growth regulators. Enhanced yield quality and increased awareness were the most significant contributors, underscoring their critical roles in promoting PGR usage.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declares that NO generative AI technologies such as large language models(ChatGPT, COPILOT, etc.) and text-to-image generators have been used during writing or editing of manuscripts.

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