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Research Paper

Brand preference towards plant growth regulator amongvegetable growers in Junagadh district of Gujarat

Niraj Kumar*[1], Ranju Nagesia*[2] andKartik Sharma[2]

[1]*P.G. Institute of Agri-Business Management, Junagadh Agricultural University, Junagadh (Gujarat) India*
[2]*ASPEE Agri-Business Management Institute, Navsari Agricultural University, Navsari (Gujarat) India*
**Corresponding author*

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ABSTRACT: *Consumer brand preference is an essential step towards understanding consumer choice behaviour, and has therefore always received great attention from marketers.It refers to the inclination of consumers to choose one brand over others in the market. Understanding brand preference is crucial for businesses as it directly influences consumer purchasing behavior and brand loyalty.This study aimed to determine the factors influencing farmers' brand preferences for plant growth regulators. Using a multi-stage sampling technique, two talukas in the Junagadh district, Junagadh and Vanthaliwere purposefully selected. A total of 160 farmers were sampled, with 80 farmers from each taluka.The factor analysis was employed to analyze the results. The principal component analysis extracted 5 factors, with the first factor explaining 29.110 per cent of the variance. Cumulatively the 5 factors accounted for 89.336 per centof the total variance. Brand preference is significantly influenced by product quality, additional features, recommendations, financial considerations, and accessibility. Farmers prioritize high-quality, effective PGRs that enhance crop health and yield, while being influenced by trusted recommendations and financial affordability.*

KEYWORDS: *Plant growth regulators, vegetables, brand preference, factor analysis andKaiser-Meyer-Olkin*

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I. INTRODUCTION

In the realm of agricultural innovation, plant growth regulators (PGRs) have emerged as a critical tool for enhancing crop yield and quality. These chemical substances, when applied in precise quantities, can significantly influence plant growth processes such as flowering, fruiting, and maturation. Among vegetable growers, the adoption of PGRs is particularly pertinent due to the high value and perishability of vegetable crops. Consequently, understanding the brand preference for these regulators is essential for manufacturers and agricultural policymakers aiming to support and optimize vegetable production. For vegetable growers, who often operate under tight economic margins and are susceptible to market and environmental fluctuations, the choice of a reliable and effective PGR brand can be a decisive factor in their overall productivity and profitability. Additionally, with the increasing emphasis on sustainable farming practices, brands that align with these values may gain preferential standing among farmers. Plant growth regulators (PGRs) or phytohormones are organic compounds, other than nutrients, that produced naturally in higher plants, controlling growth or other physiological functions at a site remote from its place of production and active in minute amounts, modify plant physiological process. PGRs called bio-stimulants or bio inhibitors, act inside plant cells to stimulate or inhibit specific enzymes or enzymes systems and help regulate plant metabolism. They normally are active at very low concentrations in plants. Plant growth regulators generally include auxins, gibberellins, cytokinin's, ethylene, growth retardants and growth inhibitors. Auxins are the hormones first discovered in plants and later gibberellins and cytokinin's were also discovered [1]. Thimann (1963) designated the plant hormones by the term 'phytohormones' (as these hormones are synthesized in plants) in order to distinguish them from animal hormones. He defined a phytohormone as "an organic compound produced naturally in higher plants, controlling growth or other physiological functions at a site remote from its place of production and active in minute amounts" [2].

Phytohormones or plant hormones, are naturally occurring substances that are produced by plants and aid in the regulation of plant growth. Additionally, they are extremely versatile chemical controllers of plant growth. When these substances are generated, they are known as Plant Growth Regulators (PGRs). Rademacher reported these findings. Internal plant hormones as well as artificial substances that have physiological properties akin to those of plant growth hormones or that can alter plant development in other ways are categorized as plant growth regulators. They are split up into two categories: Growth inhibitors (ethylene and abscisic acid) and growth promoters (auxins, gibberellins and cytokinin) [3].

Vegetable production in India is a vital component of the agricultural landscape, providing nutrition and livelihood to millions. While challenges persist, the sector's future is bright, driven by advancements in technology, government support, and a resilient farming community. Continued efforts in improving infrastructure, adopting sustainable practices, and enhancing market linkages will be crucial in realizing the full potential of vegetable production in India. India's diverse climate ensures the availability of all varieties of fresh fruits & vegetables. It ranks second in fruits and vegetable production in the world, after China. As per National Horticulture Database (2nd Advance Estimates) published by National Horticulture Board, during 2023-24, India produced 112.62 million metric tonnes of fruits and 204.96 million metric tonnes of vegetables. The area under cultivation of fruits stood at 7.04 million hectares while vegetables were cultivated at 11.11 million hectares. According to FAO (2022), India is the largest producer of Onions, ginger and okra among vegetables and ranks second in the production of Potatoes, Cauliflowers, Brinjal, Cabbages, *etc.* [4].

Factor Analysis is a multivariate statistical technique applied to a single set of variables when the investigator is interested in determining which variables in the set form logical subsets that are relatively independent of one another [5]. In other words, factor analysis is particularly useful to identify the factors underlying the variables by means of clubbing related variables in the same factor [6].

Consumer brand preference is an essential step in understanding consumer brand choice; has therefore always received great attention from marketers. Horsky *et al.* (2006) demonstrated the importance of incorporating information about brand preference into the brand choice model [7]. Brand preferences represent consumer dispositions to favour a particular brand [8]. It refers to the behavioural tendencies reflecting the extent to which consumers favour one brand over another [9]. Brand preference is close to reality in terms of reflecting consumer evaluation of brands. In the marketplace, consumers often face situations of selecting from several options [10]. Consumer preferences for brands reflect three responses: cognitive, affective and conative or behavioural [11]. The cognitive components encompass the utilitarian beliefs of brand elements. The affective responses refer to the degree of liking or favoring that reflects consumer feelings towards the brand. The conative or behavioural tendencies are denoted by Zajonc and Markus (1982) [12] as the consumers' predicted or approached act towards the object. It is the revealed preference exhibited in consumers' choices [13].

Chernev *et al.* (2011) assumes that the association of behavioural outcome, such as willingness to pay and brand preference. These are assumed to be associated with the behavioural tendencies [14]. Purchasing decisions are the behavioural outcome that precedes differentiation between several alternatives is the purchasing decision; a subsequent outcome of consumer preferences. Preferences facilitate consumers' choice by enhancing their intentions towards the favoured brand. Actual purchasing behaviour is likely to correspond to intentions; the mechanism of intention formation provides evidence of persistent consumer preferences [15]. The consistency between consumer preferences and choices adds to the predictive validity of preference statement over attitude [16]. Cobb-Walgren et al. (1995) report that attitude is a poor indicator of marketplace behaviour [17].

II. MATERIAL AND METHOD(S)

2.1 Sampling design

The current experiment utilized a multistage sampling approach to select the final sample units. In the first stage, the Junagadh district of Gujarat was purposefully chosen due to the company's interest in establishing a market presence there, making it a relevant location to determine the factors influencing farmers' brand preference for plant growth regulators. In the second stage, the talukas of Junagadh and Vanthali within the district were purposefully selected based on the company's market development strategy. The third stage involved selecting villages from these talukas, with 16 villages from Junagadh taluka and 16 villages from Vanthali taluka randomly chosen to ensure a representative sample. Finally, in the fourth stage, 5 vegetable growers from each selected village who use plant growth regulators were purposely chosen to participate in the study. This resulted in a total of 80 farmers from Junagadh taluka and 80 farmers from Vanthali taluka, comprising a sample of 160 farmers across the district.

2.2 Analytical tool

2.2.1 Factor Analysis

Factor analysis was used to find out the factors influencing brand preference by farmers for plant growth regulators. Factor 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. Factor analysis searches for such joint variations in response to unobserved latent variables. The observed variables are modelled as linear combinations of the potential factors, plus "error" terms. The information gained about the interdependencies between observed variables can be used later to reduce the set of variables in a dataset [18].

Factor analysis model

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

Where,

Xi = i^{th} Standardized variable
Aij =Standardized multiple regression coefficient of variable i on common factor j
F = Common factor
Vi = Standardized regression coefficient of variable i on unique factor i
Ui = Unique factor for variable i
m = Number of common factors

The unique factors are uncorrelated with each other and with the common factor. The common factor themselves can be expressed as linear combination of observed variable.

The unique factor model is expressed as below

$$\boldsymbol{F_i} = \boldsymbol{W_{i1}X_1} + \boldsymbol{W_{i2}X_2} + \boldsymbol{W_{i3}X_3} + \ldots \ldots + \boldsymbol{W_{ik}X_k}$$

Where,

F_i= Estimate of i^{th} factor
W_i= Weight or factor score coefficient
K= Number of variables (Zalavadiya, D. and Mishra, S. 2023)[19].

It is possible to select weights or factor score coefficients so that the first factorexplains the largest portion of the total variance. 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. This same principle could be applied to selecting additional weights for the additional factors. 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 [20].

III. RESULTS AND DISCUSSION

3.1Factor analysis

In this section the results obtained with the statistical software SPSS are presented.Factor analysis was used to find out the factors influencing brand preference by farmers for plant growth regulators. Factor 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. Factor analysis searches for such joint variations in response to unobserved latent variables.

3.1.1 KMO and Bartlett's Test: Based on the Table 2, it was interpreted as followed.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO): The KMO value in this case was 0.708, which exceeded the minimum threshold of 0.50 (Sharma, 1996) [21] and 0.60 (Kaiser and Rice, 1974) [22]. It indicated a sufficient degree of correlation among the variables, suggesting that the data was suitable for principal component analysis. The value of 0.846 suggested that the sample size was adequate for conducting the factor 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 factor 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 5293.750 with 253 degrees of freedom. The p-value was very small (.000), indicated that the correlation matrix was not an identity matrix, further supporting the suitability of the data for principal component analysis.

Table 1 KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.846
Bartlett's Test of Sphericity	Approx. Chi-Square	5293.750
	df	253
	Sig.	.000

3.1.2 Communalities

Based on Table 2, the communalities represented the shared variance between each statement and the other statements. After extraction, the communalities ranged from 0.743 to 0.980, suggesting different levels of association with underlying factors.

Table 2 Communalities of the factor analysis

Communalities		
Factor	**Initial**	**Extraction**
Quantity	1.000	.976
Product quality	1.000	.980
Price	1.000	.967
Discount	1.000	.870
Credit availability	1.000	.865
Packaging	1.000	.942
Timely availability	1.000	.918
Convenient accessibility	1.000	.972
Expiry period	1.000	.893
Brand image	1.000	.927
Farmer knowledge	1.000	.904
Advertisement by company	1.000	.963
Recommendation by dealers	1.000	.862
Recommendation by co-farmers	1.000	.743
Recommendation by local extension agent	1.000	.829
Past experience	1.000	.744
Possibility of mixing with other chemicals	1.000	.906
Affordability to use	1.000	.888
Easy process of preparation for use	1.000	.928
Resistant to diseases	1.000	.900
Overall crop health	1.000	.845
Result	1.000	.917
Effectiveness	1.000	.807
Extraction Method: Principal Component Analysis.		

3.1.3 Total Variance Explained

The Table 3, showed the initial eigen values and the rotated sums of squared loadings for each component. The components were numbered from 1 to 23. 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 (Pasini, 2017) [23]. Accordingly, the extraction of PCs was based on components with eigen values greater than 1. Based on this rule, it was clear from Table 3 that the first five components had their eigenvalues over 1 and were large enough to be retained.

The first component had the highest eigenvalue (6.695), accounting for most of the variation in the data set (29.110%). After rotation, this component's eigenvalue was 5.379, explaining 23.387 per cent of the variance. This indicates that the first component captures a substantial portion of the variability in farmers' brand preferences for plant growth regulators. The second component had an initial eigenvalue of 5.274, accounting for 22.929 per cent of the variance, and after rotation, its eigenvalue was 4.598, accounting for 19.990 per cent of the variance. This component adds significantly to the understanding of the factors influencing brand preference, highlighting another dimension of variability in the data. The third component had an initial eigenvalue of 3.291, accounting for 14.310 per cent of the total variance, and a rotated eigenvalue of 4.164, accounting for 18.104 per cent of the variance. This suggests that the third component also plays a crucial role in explaining the variations in brand preferences among farmers.

The fourth component had an initial eigenvalue of 2.857, accounting for 12.423 per cent of the total variance, and a rotated eigenvalue of 3.593, explaining 15.621 per cent of the variance. This component further elucidates the different factors that influence farmers' decisions when selecting a brand of plant growth regulator. The fifth component's initial eigenvalue was 2.430, accounting for 10.565 per cent of the total variance, with a rotated eigenvalue of 2.814, accounting for 12.235 per cent of the variance. This final significant component completes the comprehensive understanding of the multifaceted factors influencing brand preferences. Together, these five components explained a cumulative variance of 89.336 per cent in the data.

This analysis indicates that the 23 original variables related to the brand preference of farmers towards plant growth regulators were effectively reduced to five underlying factors. These five components together explained 89.336 per cent of the variance in the data, suggesting a multidimensional construct underlying farmers' brand preferences for plant growth regulators. The high cumulative variance explained by these components indicates that these factors comprehensively capture the various dimensions of farmers' brand preferences.

Table 3 Total Variance Explained

Total Variance Explained						
Component	**Initial Eigenvalues**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	**6.695**	29.110	29.110	5.379	23.387	23.387
2	**5.274**	22.929	52.039	4.598	19.990	43.377
3	**3.291**	14.310	66.348	4.164	18.104	61.481
4	**2.857**	12.423	78.772	3.593	15.621	77.101
5	**2.430**	**10.565**	**89.336**	**2.814**	**12.235**	**89.336**
6	.355	1.542	90.878			
7	.289	1.258	92.135			
8	.250	1.087	93.223			
9	.229	.995	94.218			
10	.203	.883	95.101			
11	.187	.812	95.913			
12	.161	.698	96.611			
13	.142	.618	97.229			
14	.127	.553	97.782			
15	.109	.476	98.258			
16	.097	.421	98.679			
17	.083	.359	99.038			
18	.062	.270	99.308			
19	.043	.188	99.495			
20	.041	.177	99.672			
21	.038	.166	99.838			
22	.027	.117	99.955			
23	.010	.045	100.000			
Extraction Method: Principal Component Analysis.						

3.1.4 Factor extraction with the scree plot

The factor extraction with the scree plot (Cattell, 1966; Horn and Engstrom, 1979), showed decreasing eigenvalues on the y-axis and the relevant number of components on the x-axis. The Kaiser rule of eigenvalues greater than 1 was used as a supplementary objective criterion or “stopping rule” for retaining components (Henson and Roberts, 2006[24]; Ruscio and Roche, 2012[25]). As shown in Figure 1, using this rule, point y = 1 on the graph represented the Kaiser criterion cut-off point, according to which five components satisfied this rule and were retained; the other factors starting from the sixth were thereby ignored and were subsequently excluded from the model.

A scree plot graphs eigenvalue magnitudes on the vertical access, with eigenvalue numbers constituting the horizontal axis. The eigenvalues are plotted as dots within the graph, and a line connects successive values. Factor extraction should be stopped at the point where there is an ‘elbow’ or leveling of the plot. This test is used to identify the optimum number of factors that can be extracted before the amount of unique variance begins to dominate the common variance structure [26] [27].

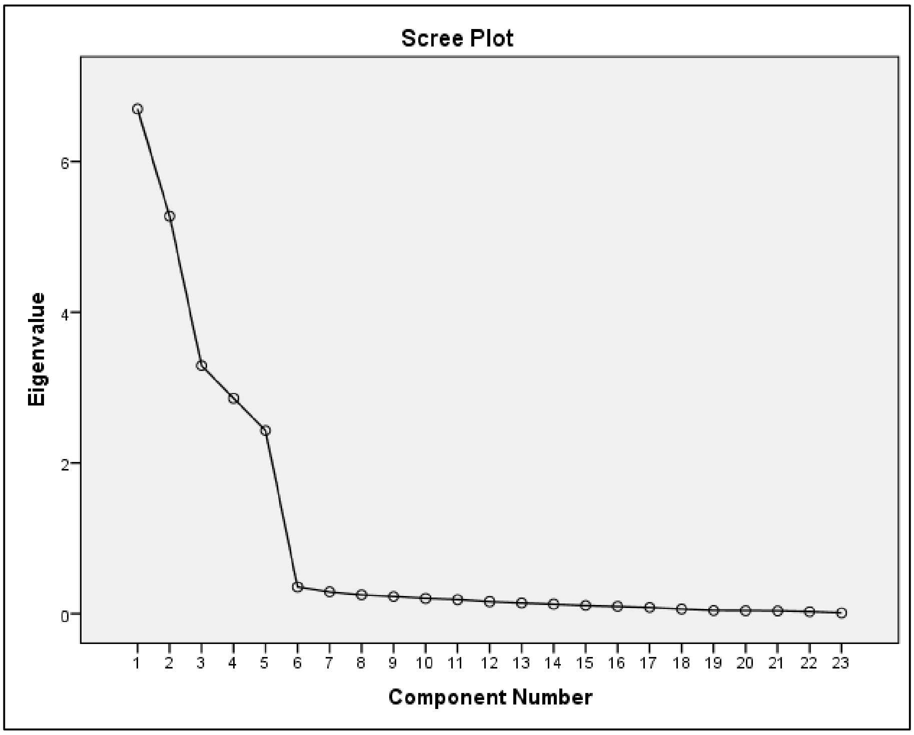

Fig 1 Scree plot for eigenvalues

3.1.5 Component Transformation Matrix

This component transformation matrix Table 4, provided the transformation coefficients used to obtain the rotated component matrix from the initial component matrix. Each row represented a component, and each column represented a rotated component. The matrix showed the loadings or weights assigned to each variable (components 1 to 5) in each of the extracted components (1 to 5). These loadings indicated the degree to which each variable contributed to a particular component. The values in each cell indicated the relationship between the initial component and the rotated component. These coefficients were useful for interpreting the rotated component matrix and understanding the relationships between the original components and the rotated components.

Table 4 Component Transformation Matrix

Component Transformation Matrix					
Component	**1**	**2**	**3**	**4**	**5**
1	-.752	.596	.119	.253	.041
2	.395	.432	.749	-.228	.210
3	.233	-.148	.250	.928	-.020
4	.329	.497	-.232	.043	-.767
5	.340	.436	-.555	.146	.604

3.1.6 Rotation of the Components

The Table 5, presented the rotated component matrix after performing a varimax rotation. A rotation was a linear transformation that was performed on the initial factor solution for the purpose of making an easier interpretation (Constantin, 2014) [28]. Various approaches for the rotation of the components had been proposed

(Hilbert and Buehner, 2017[29]; Tabachnick and Fidell, 2007[30]). The most common rotation method was orthogonal varimax (Constantin, 2014), which was applied in the current study obtained 5 components from 23 variables; Only the variables with a factor loading greater than 0.50 were included as factors following the recommendations of (Costello and Osborne 2005) [31]; variables with factor loadings below 0.5 were eliminated.

Table 5 Rotated Component Matrix

Rotated Component Matrix					
Factors	**Component**				
	1	**2**	**3**	**4**	**5**
Product quality	**.974**	-.134	.061	-.103	-.005
Packaging	**.951**	-.127	.090	-.116	-.010
Resistant to diseases	**.940**	-.068	.084	-.057	.025
Expiry period	**.930**	-.139	.068	-.057	.018
Overall crop health	**.902**	-.126	.037	-.118	.017
Effectiveness	**.878**	-.176	-.007	-.044	-.055
Quantity	-.170	**.963**	.138	.019	.023
Brand image	-.090	**.947**	.145	-.009	.018
Possibility of mixing with other chemicals	-.088	**.935**	.151	-.008	.021
Result	-.199	**.927**	.125	.048	.023
Farmer knowledge	-.199	**.921**	.106	.069	.011
Advertisement by company	.031	.141	**.968**	-.017	.069
Recommendation by dealers	.033	.082	**.922**	.013	.068
Recommendation by local extension agent	.061	.127	**.896**	-.039	.071
Recommendation by co-farmers	.057	.101	**.854**	-.015	.026
Past experience	.107	.166	**.837**	-.022	.067
Price	-.155	.028	-.011	**.971**	-.013
Affordability to use	-.119	.022	-.031	**.934**	.024
Discount	-.048	.004	-.029	**.931**	-.018
Credit availability	-.083	.044	-.001	**.924**	-.056
Convenient accessibility	-.012	.016	.091	-.032	**.981**
Timely availability	.004	.048	.031	.010	**.956**
Easy process of preparation for use	-.001	.009	.139	-.039	**.952**
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization					
a. Rotation converged in 5 iterations.					

3.1.7 Labelling of the factors

Each of the fivefactors included in Table 6 were labelled with an appropriate name according to the components that loaded most highly for that dimension (see Table 5).

Overall, the results showed that the factor 1-Product and quality and factor 2-Additional features and benefits and factor 3-Recommendations and influence were the most influential factors to determine the factors influencing farmers' brand preferences for plant growth regulators because of their highest per cent of variance as mentioned in the Table 3.

Table 6 Labelling of components

Factor number	**Factor name**	**Variables under factor**	**Factor loading**
1	Product and quality	Product quality	.974
		Packaging	.951
		Resistant to diseases	.940
		Expiry period	.930
		Overall crop health	.902
		Effectiveness	.878
2	Additional features and benefits	Quantity	.963
		Brand image	.947
		Possibility of mixing with other chemicals	.935
		Result	.927
		Farmer knowledge	.921
3	Recommendations and influence	Advertisement by company	.968
		Recommendation by dealers	.922
		Recommendation by local extension agent	.896
		Recommendation by co-farmers	.854
		Past experience	.837
4	Price and financial considerations	Price	.971

		Affordability to use	.934
		Discount	.931
		Credit availability	.924
5	Availability and accessibility	Convenient accessibility	.981
		Timely availability	.956
		Easy process of preparation for use	.952

Factor 1 -Product and Quality: This factor included variables such as product quality (.974), packaging (.951), resistance to diseases (.940), expiry period (.930), overall crop health (.902), and effectiveness (.878). Farmers prioritize the inherent quality and performance of PGRs because these factors directly impact crop yield and health. High-quality products are more likely to enhance crop growth, resist diseases, and ensure a longer shelf life (expiry period). Effective PGRs improve overall crop health, which is crucial for maximizing production and profitability. Good packaging protects the product from contamination and degradation, thereby maintaining its effectiveness over time.

Factor2 - Additional Features and Benefits: The variables under this factor were quantity (.963), brand image (.947), possibility of mixing with other chemicals (.935), result (.927), and farmer knowledge (.921). Additional features and benefits offer practical and perceived value to the farmers. Quantity indicates the volume of PGRs available for use, which can be economical for larger farms. A strong brand image often reflects trustworthiness and reliability, encouraging farmers to prefer well-known brands. The ability to mix PGRs with other chemicals is crucial for integrated pest management practices, enhancing overall farm productivity. Positive results and knowledge about the PGR's performance help farmers make informed decisions, ensuring they choose products that consistently deliver desirable outcomes.

Factor3 -Recommendations and Influence: This factor encompassed advertisement by the company (.968), recommendation by dealers (.922), recommendation by local extension agents (.896), recommendation by co-farmers (.854), and past experience (.837). Social and professional influences significantly shape farmers' decisions. Company advertisements provide information and create awareness about the PGRs' benefits and features. Recommendations from trusted sources like dealers, local extension agents, and fellow farmers serve as endorsements, increasing the credibility of the product. Past positive experiences reinforce brand loyalty, as farmers tend to stick with products that have previously yielded good results.

Factor4 - Price and Financial Considerations: The price (.971), affordability (.934), discount (.931), and credit availability (.924) were the variables under this factor. Financial aspects are critical in decision-making as they directly affect the cost of production and profitability. Farmers often operate on tight budgets, making the price of PGRs a significant factor. Affordability ensures that farmers can consistently purchase and use the product without financial strain. Discounts and credit availability provide financial flexibility, allowing farmers to manage their cash flow better and invest in other necessary inputs for their farms.

Factor5 -Availability and Accessibility: This factor included convenient accessibility (.981), timely availability (.956), and easy process of preparation for use (.952). The practical aspects of obtaining and using PGRs are essential for efficient farm management. Convenient accessibility ensures that farmers can easily acquire the product when needed, reducing downtime and logistical challenges. Timely availability is crucial for aligning the application of PGRs with critical growth stages of the crops, maximizing their effectiveness. An easy preparation process for use simplifies farm operations, making it more likely that the farmers will use the product correctly and consistently.

IV. CONCLUSION

Brand preference plays a pivotal role in the competitive landscape of modern business. It's not merely about immediate sales but about cultivating a long-term relationship with consumers.Key determinants such as product quality, additional features, recommendations, financial considerations, and accessibility play pivotal roles in shaping farmers' preferences.Farmers prioritize high-quality PGRs that enhance crop health and yield, with additional benefits like compatibility with other chemicals and brand reputation further influencing their choices. Recommendations from trusted sources and positive past experiences significantly sway their decisions. Financial considerations, including price, affordability, discounts, and credit availability, reflect the economic realities faced by farmers, making them crucial in the decision-making process. Lastly, the ease of access and timely availability of PGRs are essential for practical and efficient farm management.By considering the diverse factors identified, stakeholders can develop and promote PGRs that better align with the priorities of vegetable growers in the region. Implementing strategies that focus on product quality and performance, enhance additional features, leverage social and professional influence, consider financial flexibility, improve accessibility and convenience and conduct continual research and feedback can enhance the adoption and satisfaction of PGRs. Ultimately, these efforts will contribute to improved agricultural productivity and sustainability in Junagadh district.

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COMPETING INTERESTS

Authors have declared that no competing interest exist.

REFERENCES

[1]. Bisht, T. S.; Rawat, L.; Chakraborty, B. and and Yadav, V. 2018. A Recent Advances in Use of Plant Growth Regulators (PGRs) in Fruit Crops - A Review. International Journal of Current Microbiology and Applied Sciences.**7(5):** 1307-1336

[2]. Thimann, K. 1963. Plant Growth Substances: Past, Present and Future. Ann. Rev. Plant Physiol. **14:** 1–18.

[3]. Rademacher W. 2015. Plant growth regulators: Backgrounds and uses in plant production. Journal of Plant Growth Regulators. **34:**845-872.

[4]. Anonymous. 2024. Agricultural and Processed Food Products Export Development Authority (APEDA), Fresh Fruits & Vegetables. Available at <https://apeda.gov.in/apedawebsite/about_apeda/About_apeda.htm>last accessed on 24th March, 2024.

[5]. Tabachnick, B.G. and Fidell, L.S., Using multivariate statistics (6th ed.), Pearson, 2013.

[6]. Verma, J. and Abdel-Salam, A., Testing statistical assumptions in research, John Willey & Sons Inc., 2019.

[7]. Horsky, D.; Misra, S. and Nelson, P. 2006. Observed and unobserved preference heterogeneity in brand-choice models.Marketing Science.**25(4):** 322-335.

[8]. Overby, J. W. and Lee, Eun-Ju. 2006. The effect of utilitarian and hedonic online shopping value on consumer preference and intentions. Journal of Business Research.**59(10):** 1160-1166.

[9]. Hellier, P.K.;Geursen, G.M.; Carr, R.A. and Rickard, J.A. 2003. Customer repurchase intention: A general structural equation model.European Journal of Marketing.**37(11/12):** 1763.

[10]. Dhar, R.;Nowlis, S. M. and Sherman, S. J. 1999. Comparison effects on preference construction.Journal of Consumer Research. **26(3):** 293-306.

[11]. Grimm, P.E. 2005. Ab components impact on brand preference.Journal of Business Research.**58(4):** 508-517.

[12]. Zajonc, R.B. and Markus, H. 1982. Affective and cognitive factors in preferences.Journal of Consumer Research.**9(2):** 123-131.

[13]. Hsee, C.K.; Yang, Y.; Gu, Y. and Chen, J. 2009. Specification seeking: How product specifications influence consumer preference.Journal of Consumer Research.**35:** 952- 966.

[14]. Chernev, A.; Hamilton, R. and Gal, D. 2011. Competing for consumer identity: limits to self-expression and the perils of lifestyle branding. Journal of Marketing.**75(3):** 66- 82.

[15]. Van Kerckhove, A.;Geuens, M. and Vermier, I. 2012. Intention superiority perspectives on preference-decision consistency.Journal of Business Research.**65(5):**692-700.

[16]. Bither, S.W. and Wright, P. 1977. Preferences between product consultants: choices vs. preference functions. Journal of Consumer Research.**4(1):** 39-47.

[17]. Cobb-Walgren, C.J.; Ruble, Cynthia A. and Donthu, N. 1995. Brand equity, brand preference, and purchase intent. Journal of Advertising.**24(3):** 26-40.

[18]. Thurstone, L. 1931. Multiple factor analysis. Psychological Review.**38(5):** 406-427.

[19]. Zalavadiya, D. and Mishra, S. 2023. Awareness and brand preference of chickpea growers towards selected pesticides in Junagadh district of Gujarat, India. Asian Journal of Agricultural Extension, Economics & Sociology.**41(9):** 486-494

[20]. Nagaral, A. 2018. A study on pesticide brand preference of pomegranate grower's in Tumakuru district of Karnataka. MBA (Agri-Business). Thesis (Unpublished). University of Agricultural Sciences, Bengaluru.

[21]. Sharma, S. 1996. Applied Multivariate Techniques. Journal of Marketing Research.**18(3):** 291-300.

[22]. Kaiser, H. F. and Rice, J. 1974. Little jiffy, mark IV. Educational and Psychological Measurement.**34(1):** 111-117.

[23]. Pasini, G. 2017. Principal component analysis for stock portfolio management. International Journal of Pure and Applied Mathematics.**115(1):** 153-167.

[24]. Henson, R. K. and Roberts, J. K. 2006. Use of exploratory factor analysis in published research: Common errors and some comment on improved practice. Educational and Psychological Measurement.**66(3):** 393-416.

[25]. Ruscio, J. and Roche, B. 2012. Determining the number of factors to retain in an exploratory factor analysis using comparison data of known factorial structure. Psychological Assessment.**24(2):** 282-292.

[26]. Thompson, B. and Washington D.C., 2004. Exploratory and confirmatory factor analysis: Understanding concepts and application.American Psychological Association.

[27]. Cattell, R.B. 1996. "The scree test for the number of factors," Multivariate Behavioral Research. **1:** 245-276.

[28]. Constantin, C. 2014. Principal component analysis: A powerful tool in computing marketing information. Bulletin of the Transilvania University of Brasov. **7(56-2):** 25-30.

[29]. Hilbert, S. and Buehner, M. 2017. Principal components analysis. Encyclopedia of Personality and Individual Differences.**5(5):** 1-50.

[30]. Tabachnick, B. G. and Fidell, L. S. 2007. Using multivariate statistics. (5th ed.). Strategies for reducing consumers' risk aversion in internet shopping. Journal of Consumer Marketing. **16(2):** 163-180.

[31]. Costello, A. B. and Osborne, J. W. 2005. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. Practical Assessment Research and Evaluation. **10(7):** 1-8.